Assessing the Relevance of Context for Visualizations of Movement Trajectories

Dissertation

zur

Erlangung der naturwissenschaftlichen Doktorwürde

(Dr. sc. nat.)

vorgelegt der

Mathematisch-naturwissenschaftlichen Fakultät

der

Universität Zürich

von

Anna-Katharina Lautenschütz

aus

Deutschland

Promotionskomitee

Prof. Dr. Sara Irina Fabrikant (Vorsitz)

Prof. Dr. Mary Hegarty

Dr. Tumasch Reichenbacher

Prof. Dr. Robert Weibel

Zürich 2011

Abstract

Large amounts of moving point data are generated daily through technological devices, such as GPS, digital navigation aids, or mobile phones. The analysis of movement data has become a hot topic in Geographic Information Science and related fields, such as ecology, with the aim to understand movement processes and movement behavior. Current data mining and visualization approaches focus on the algorithmic description of movement parameters to identify patterns. The context of the moving object, e.g. the environment in which the movement takes place, as well as the context of the analyst, such as their previous knowledge and perceptual skills, are only weakly considered when exploring, analyzing, and representing movement data.

A cognitive conceptual framework is based on theoretical foundations from geographic information science, visualization research, and cognitive science, and specifically integrates cognitive science into the data collection and data visualization cycle. The development of the framework helps to get an understanding how humans process and conceptualize visualizations of movement.

Three human subject experiments assess the influence of context information for the understanding of movement visualizations. In these experiments, context is defined as the geographic context of the moving object, as well as additional relevant information about the object and its behavior. The results suggest that the inclusion of context information is dependent on the analysts' task. The identification of basic movement parameters, such as speed, distance, direction, or velocity, does not require context information in visual displays. However, to understand certain movement behavior, e.g. an animal searching for food, context information helps to understand visualizations of movement. Specifically integrating geographic context information of the object is a useful step to help analysts understand movement processes and movement behavior, and to ultimately be able to give design guidelines for cognitively inspired visualizations of movement.

Zusammenfassung

GPS, Mobiltelefone, und Navigationshilfen generieren täglich eine Vielzahl von Bewegungsdaten. Der Analyse von Bewegungsdaten wird heute immer mehr Beachtung in der Geographischen Informationswissenschaft und benachbarten Wissenschaften, wie z.B. Verhaltensbiologie, geschenkt. Die Auswertung grösserer Datenmengen mit Algorithmen und Visualisierungen fokussiert dabei vor allem auf der geometrischen Beschreibung von Bewegungscharakteristiken, wie z.B. Geschwindigkeitswechsel. Dabei wird weder der Kontext des bewegenden Objektes, z.B. die Umgebung des Objektes, noch der Kontext des Benutzers, z.b. dessen Vorwissen wie auch perzeptiven Fähigkeiten, ausreichend beachtet.

Das kognitive Rahmenmodel dieser Arbeit basiert auf Theorien aus der Geographischen Informationswissenschaft und der Kognitionswissenschaft und versucht einen Weg aufzuzeigen, wie die kognitiven Fähigkeiten des Benutzers integriert werden können, um Visualisierungen von Bewegungen zu verbessern.

Drei Nutzerstudien messen den Einfluss von Kontext auf das Verständnis von Visualisierungen von Bewegungsdaten. In diesen Experimenten wird Kontext zuerst als zusätzliche, relevante Information, und dann als geographischen Kontext, in diesem Fall durch eine Höhenkarte, definiert. Die Ergebnisse erlauben die Annahme, dass Kontext eine wichtige Rolle spielt wenn Nutzer ein Objekt und die entsprechende Bewegung identifizieren sollen. Kontext spielt anscheinend jedoch eine geringere Rolle, wenn der Nutzer die geometrischen Bewegungscharakteristiken, wie z.B. ein Geschwindigkeitswechsel, erkennen soll. Für die Erkennung von Bewegungsmustern heisst das, dass generische Bewegungsmuster, die auf geometrischen Bewegungscharakteristiken beruhen keine zusätzliche Kontextinformation brauchen. Die Identifikation von speziellen Bewegungsmustern, wie z.B. Futtersuche bei Tieren, wird jedoch enorm erleichtert, wenn Kontextinformation vorhanden ist.

Acknowledgements

This thesis would not have been possible without the guidance, support, understanding, and help from a lot of people. I would like to express my highest gratitude to these people.

I would like to thank my supervisor Prof. Dr. Sara Fabrikant for giving me the chance to conduct this research within her research project "PopEye". Her contribution of time, encouragement, and patience has been invaluable to the maturation of my thesis. The Swiss National Science Foundation funded this project. I would like to thank Prof. Dr. Robert Weibel for his enthusiasm about context and his support. I would also like to thank Prof. Dr. Mary Hegarty for sharing her time and her expertise on human subject experiments. Also, I would like to thank her for her warm welcome and her support while working at UCSB. My heartfelt thanks also go to Dr. Tumasch Reichenbacher, who stepped in as co-advisor when needed and always provided me with thoughtful discussions, advise, and constructive criticism.

Many people of the Department of Geography assisted, supported, and inspired me in various ways, and I would like to thank the colleagues from GIVA and GIS for their discussions. Many thanks go to Dr. Ross Purves, who always has an open ear, and whose helpful advise, comments, and discussions allowed the finishing of this thesis. I particularly thank Ramya Venkateswaran for her programming expertise and her encouragement while setting up the third experiment, and Stefano de Sabbata for helping me aggregate my data files. I would like to extend my thanks to my office mate Jan Wilkening for sharing the ups and downs during the PhD. My heartfelt thanks go to Arzu Cöltekin, who always had an ear for my concerns, and who guided me on my way through academia with her expertise. I would like to thank Somayeh Dodge for being such a welcoming friend and project partner, for fun and crucial times throughout my time at GIUZ. Additonally, I would like to thank Ralph Straumann for his randomization ideas, discussions, and encouragement. I would like to extend my thank to Kenan Bektas, Pia Bereuter, David Caduff, Paul Crease, Patrick Laube, Patrick Lüscher, Frank Ostermann, Marco Salvini, Ronald Schmidt, and Martin Tomko for their contributions and discussions.

I would like to thank Reto Zupf and Daniel Köchli from the ZHAW Wädenswil for the permission to use movement data from the Mafreina Project. I would like to extend my appreciation to the participants of these experiments for their time.

Finally, I would like to thank my parents for their loving upbringing, for their encouragement to do a PhD in Switzerland, as well as their emotional support throughout the years. I thank my brother Benedikt and my sister Julia for endless phone calls, bike rides, visits, and motivation. Special thanks go to my friends, Jacqueline, Manuela, Nina, and Stefanie for their constant encouragement, especially in rough times! Last but not least, I thank Damian Blarer for his endless support, motivation, patience, interest, and love. You kept me grounded at all times and shared life with me besides academics. It would not have been possible without you! Thank you!

Content

List of Figures

List of Tables

Introduction

Every process happens somewhere in space and time, such as weather, tides, migration, or traffic. Weather, for instance, is happening in the atmosphere, creating fronts that move from one place to the next, bringing us rain and sun. Animals and humans are moving on the earth's surface, to find food, places of shelter, and to communicate with one and another. Movement is a process that results in change of location through time. Movement of point objects, like animals and humans, has been the focus of interest in geography and cognate research areas for many decades. Ecologists, for instance, are interested in the behavior of animals and use radio collars and GPS devices to track animals in their natural habitat. In geography, movement research has been studied with foci in transportation geography, time geography, and spatial behavior research for the last decades. With the advances of technology, movement data can be captured easier than ever. Humans use mobile phones, digital navigation devices, or GPS to get location information. The availability of large amounts of movement data facilitates the development of various analysis methods to analyze movement data. The analysis of moving point data has become a hot topic to investigate not only what and where movement has happened, but also to get insights into why movement has happened. In ecology, for instance, the introduction of global positioning systems (GPS) and telemetry data collection methods has facilitated various successful animal behavior studies (Frair *et al.* 2010; Tomkiewicz *et al.* 2010). In Geographic Information Science (GIScience) the exploration of moving point datasets for identifying movement patterns has become a research focus (Dykes and Mountain 2003) and has led to a variety of approaches (Buchin *et al.* 2009; Dodge *et al.* 2009; Gudmundsson *et al.* 2004; Laube *et al.* 2005) and tools, such as Hawths Tools, Home Range extension, and Tracking Analyst for ESRI's ArcMap. Common to these approaches and tools is that movement data is analyzed with algorithms according to their basic movement parameters, such as speed, distance, direction and velocity (Dodge *et al.* 2008). The analysis is mainly independent of the surrounding geographic context, i.e. the location in which movement takes place, for instance, the geographic context of a moving ibex is steep terrain in an alpine setting. However, it remains an open research question if movement analysis without geographic context information allows answers to the question *why* movement is happening.

1.1 Problem Statement and Motivation

Visual analytics tools, such as GeoVista Studio (Gahegan 2001) or CommonGIS (Andrienko *et al.* 2003) have been developed based on the contention that they combine computational methods with the outstanding human capabilities for pattern recognition, imagination, association, and reasoning (Andrienko *et al.* 2003). However, exploring, extracting, and understanding the meaning encapsulated in movement data from a user perspective has become a bottleneck, especially because the inherent complex and multidimensional nature of the data has not been sufficiently integrated into visual analytics tools from a user perspective.

Only limited research has been carried out to fully integrate spatio-temporal data at the human computer interface level, that is, effectively representing spatio-temporal data to the user in a cognitively plausible way. Cognitively plausible in this context means that visualizations of movement are built on how humans perceive and process information (Fabrikant and Skupin 2005). To this point, no theory or groundwork exists that clarifies what makes a visualization cognitively plausible for analyzing movement behavior. Specifically, visual analytics has to consider how users conceptualize and understand movement data (Fabrikant *et al.* 2008a) to ensure the inclusion of cognitive principles for the integration of space-time data. One major factor to make the data more accessible for the users is the integration of context information, specifically the geographic setting in which movement takes place. This approach might be indispensable to help detect behavioral movement patterns in animal or human behavior, such as foraging, chase/escape, or fight and pursuit. Although researchers argue for the inclusion of context information, so far, only few approaches explicitly integrate context or semantic information in the analysis of movement data with the goal to identify movement patterns (Schmid *et al.* 2009; Yan *et al.* 2008).

Context can be either the context of the moving object or the analysts' context (see Figure 1). The context of the moving object are the geographic location, the influence of other objects, its movement capacity, and the spatial and temporal scale of the object and its sampling.

The geographic location of the object can be an ibex moving in alpine terrain. The geographic location of the object is crucial in mobile computing and describes context-awareness as "to provide relevant information and/or services to the user" (Dey and Abowd 2000). In a movement ecology framework introduced by Nathan et al. (2008), the geographic context is also considered one of the key elements to understand which external factors affect animal movement. The geographic location therefore seems to be a very important context element to understand movement and its behavior. It has therefore been identified as a key factor to be empirically evaluated in this thesis. The influence of other moving objects is another key aspect of context that is described in the movement ecology framework as one reason to explain the internal state of moving objects. This context factor aims at explaining why a movement is happening, e.g. because a predator is following prey. Another contextual factor is the movement capacity of an object, including its motion capacity, e.g. an ibex can run and climb but not swim, as well as its navigation capacity of an object, e.g. to where it moves. Finally, the spatial and temporal scale of an object is also considered to be the context of an object. This relates to the sampling rate of moving point data, e.g., yearly migration of birds as opposed to daily movement patterns of a butterfly.

The context of the analyst also influences the understanding of movement data (see Figure 1). Users have different degrees of previous knowledge when assessing spatio-temporal data, e.g., a behavioral ecologist is potentially trained to find home ranges, while a transportation analyst is more trained to understand the network dynamics. Additionally, an analyst's perceptual and cognitive ability also influences his/her understanding of spatio-temporal data. Two other factors that influence the user when analyzing and understanding spatio-temporal data are the analysis task and the user interface. The analysis task determines what the analyst is trying to find out, e.g. looking for home ranges or the identification of similarities between movement trajectories. The display influences how good the analyst can solve specific analyses tasks, i.e., a well-designed interface/display helps the analyst to better understand and analyze spatio-temporal data.

The analysis of movement data is therefore dependent on the analyst's context and the context of the moving object. This thesis empirically assesses the context of the moving object, and specifically whether information about the geographic location of a moving object helps the user to understand the behavior of a moving object when analyzing its trajectory. The experiments therefore aim to provide empirical evidence if context information helps analyst's to facilitate previous knowledge and perception and cognition when analyzing movement trajectories.

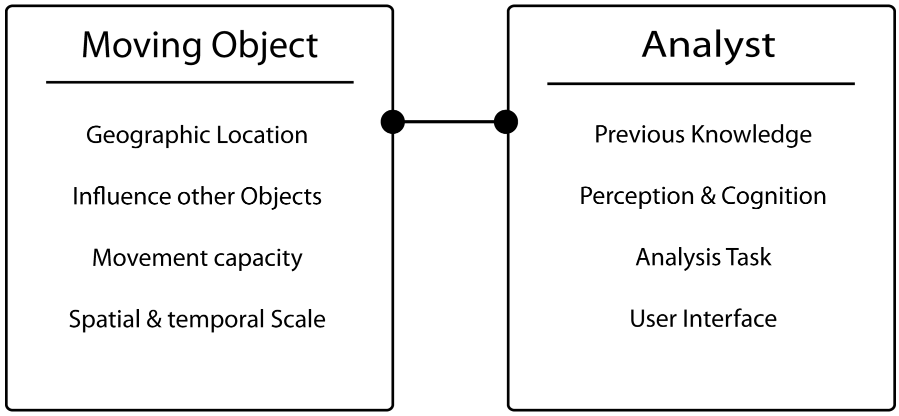


Figure 1: Context information of a moving object and a user

In order to enhance visual analytics tools by integrating cognitive principles, we have to ask to what extent cognitive factors influence our understanding, reasoning, and analysis of movement data, and which factors could enhance decision making with visual representations of movement data. It is specifically important to comprehend human's knowledge construction and reasoning about spatial and temporal phenomena and processes in order to improve visually extracting movement patterns and making informed decisions when analyzing the data. A better understanding of human cognitive processes is fundamental to facilitate sense-making of movement data, and to ultimately develop empirically validated guidelines for the construction of cognitively inspired visualizations of movement.

1.2 Aim

This dissertation project is situated at the interdisciplinary setting of geographic movement pattern research and cognitive science and is part of the larger research project "visual analytics of spatio-temporal gaze **po**int **p**atterns in **eye** movements" (Popeye). Popeye is funded by the Swiss National Fund and focuses on exploratory visualization, interaction, and evaluation and tries to identify how spatio-temporal information can be efficiently discovered, knowledge extracted and communicated in visual displays.

This thesis focuses on how humans perceive and understand graphical displays of movement data. It especially examines how visualizations of movement trajectories are understood and how the inclusion of the moving objects' context can help to understand behavioral movement patterns. As such, the work is guided by the following **hypothesis**:

Visualizations of movement data are not only dependent on the representation of basic movement parameters, but also have to consider perception and cognition of the user. The analysis of movement data is dependent on the user's context (e.g. task, previous knowledge, perception and cognition of the user) and the context of the moving object (e.g. spatial and temporal scale, relation to other moving objects, surrounding environment).

I assume that providing context information of the moving object influences the understanding of the analyst in a positive way, i.e. the analyst recognizes specific movement behavior and patterns more easily. To assess this hypothesis statement requires comparing the results from empirical investigations, i.e. three individual human subject experiments (as described in Chapter 5). The experiments of this thesis are guided by the following **overall research question**:

What is the effect of context information on the exploration and analysis of movement data?

1.3 Approach

The empirical assessment of context information can be structured into four stages (see Figure 2).

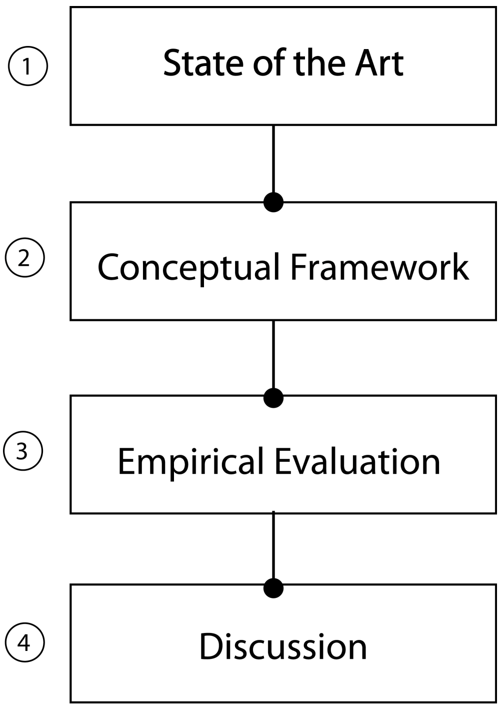


Figure 2: Workflow of the thesis

The first step (see ① in Figure 2) is a systematic investigation of relevant research from GIScience, cognitive science, and geovisualization research, and highlights theoretic principles and previous research findings. These theoretical foundations then form the basis for the development of a cognitive conceptual framework (see ② in Figure 2), which implements first findings from a taxonomy of movement patterns and expert interviews. The framework directs the subsequent human subject experiments, which are grounded in the cognitive perspective of the conceptual framework (see ③ in Figure 2). In a last step, findings from human subject experiments are discussed and integrated into the body of knowledge (see ④ in Figure 2).

The main objective of the conceptual framework is the development of a sound integrated space-time visualization component that integrates humans' understanding of spatio-temporal processes in a cognitively inspired way. Figure 3 shows the conceptual framework in more detail. The framework consists of three perspectives (see Figure 3): a data perspective and a visualization perspective that are linked by a cognitive perspective. Each of the perspectives consists of top-down and bottom-up components. The top-down components include theories and principles from existing research (as reviewed in Chapter 2) and are marked with theories at the top of Figure 3, while the bottom-up components are depicted at the bottom of the graphic and are derived from the development of the taxonomy of movement patterns (Dodge *et al.* 2008), human subject testing, as well as the design of visualizations. This thesis focuses on human subject testing within the cognitive perspective.

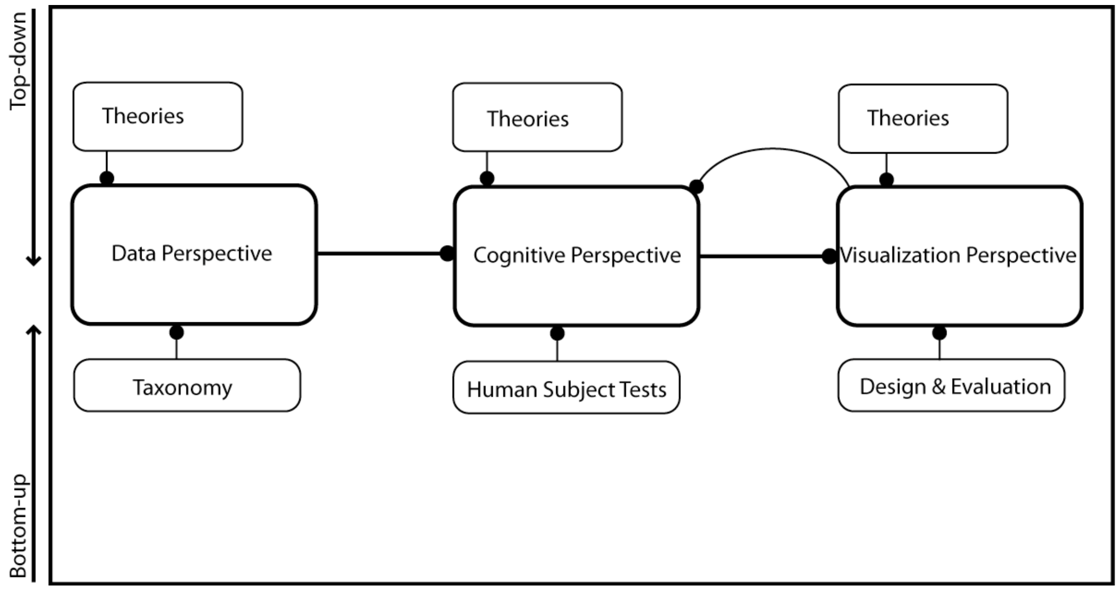


Figure 3: A cognitive conceptual framework to improve visualizations of movement

Briefly stated, the data perspective focuses on storing and modeling basic movement parameters, such as distance, direction, speed, position, velocity, instance, and interval (Dodge *et al.* 2008) and is depicted on the left side of Figure 3. The taxonomy of movement patterns (Dodge *et al.* 2008) is one of the bottom-up building blocks of the data perspective and distinguishes generic from behavioral movement parameters for automated, computer-based movement data analysis. Visual displays allow the exploration, identification, and analysis of generic and behavioral movement patterns in large amounts of movement data through cognitively inspired and perceptually salient displays as part of the visualization perspective (on the right side of Figure 3). A cognitive perspective is integrated that has largely been missing in previous work and potentially provides the missing link between data analysis and discovering knowledge in large movement databases. Systematic human subject testing within the cognitive perspective will allow evaluating existing theories and approaches for geovisualizations of movement data. Within this thesis I particularly focus on the assessment of context information for the conceptualization of spatio-temporal data in visual displays by introducing additional information about the moving object and its behavior in Experiment I, as well as adding geographic context information through a terrain map in Experiments II and III. The integration of these three perspectives is in my eyes essential to improve visualizations of moving point data for more effective and efficient spatio-temporal exploration and decision-making.

1.4 Structure of thesis

The remainder of this thesis is organized as follows:

Chapter 2 reviews theoretical research findings from geographic information science, visualization and cognitive science and identifies research gaps. **Chapter 3** introduces the conceptual framework for movement visualizations. It describes initial research steps, such as the development of a taxonomy of movement patterns and qualitative expert interviews. **Chapter 4** provides a short overview on employed experimental methods including eye movement data collection method. **Chapter 5** presents the experiments, which deal with the identification of movement parameters and the identification of object and behavior in visual displays of movement. **Chapter 6** critically discusses the research findings and the relevance of the framework. The chapter also highlights limitations of this approach. **Chapter 7** summarizes the overall findings of the thesis and concludes with the contribution of this thesis. It also highlights potential future research directions.

2. State of the Art

Various research areas have long-standing research interests in space-time phenomena and have re-discovered them recently due to the increased availability of massive movement data sets. Spatial characteristics of moving point data are either conceptualized as point or linear features with continuous, cyclical, or intermittent temporal characteristics (Yattaw 1999). The integration of spatio-temporal exploratory data analysis methods and visual analytics lies at the intersection of complementary research fields, such as GIScience (e.g., geographic information visualization, temporal GIS, spatial cognition), computer science (e.g., databases, human-computer interaction, and information visualization), and cognitive science. Based on the linkages between the proposed perspectives in the cognitive conceptual framework (see Introduction, Figure 2) the review is guided by the question to which extent cognitive issues have been integrated in various previous approaches. The review starts with relevant literature from the data perspective, and highlights research in geography and GIScience that has been moving from a more descriptive approach and analysis (i.e., analysis of movement patterns), to a more dynamic, and process-oriented approach. I then survey the geovisual analytics literature, also documenting a paradigm shift from static visualizations to interactive and dynamic displays of moving phenomena. Finally, the review presents the respective state-of-the-art literature from cognitive science research, e.g. spatio-temporal reasoning, event understanding, etc., that has been largely overlooked in GIScience research work on moving phenomena at an individual level, e.g. humans and animals.

2.1 The nexus of space and time

> *„Together, space and time form the framework for the cage within which human life unfolds“. (Haggett 2001)*

Basically all geographic movement is associated with the spatial and temporal change of an object (Yattaw 1999). Since at least the 1960s, geographers have realized that the study of spatio-temporal processes is essential to explain resulting spatial patterns, and to identify potential cause-and-effect relationships of processes, such as cities and migration (urban phenomena), human travel behavior, or land use and land cover change.

In the 1960s Hägestrand and his colleagues (Hägerstrand 1970) moved away from aggregate time-space studies to tracking individuals, which results in detailed localized movement trajectories. Since then, geography has continued investigating diffusion processes of all sorts, including human travel and migration behavior, or movements of animals and goods, and Geographic Information Systems (GIS) are increasingly used for displaying the results of the studied activity patterns (Forer and Huisman 2001; Golledge and Stimson 1997; Miller 1991; Zhao *et al.* 2008).

One of Hägestrands' core space-time concepts is the space-time prism (or cube) as shown in Figure 4. The prism is formed by two spatial dimensions (x, y) and is extended by a third dimension (z) to represent time. The two-dimensional space records the change of location of a moving object, while the third dimension is used to order the sequence of events during the movement happening over space. Truly three dimensional movement is reduced to a two dimensional space and does not take into account altitude changes, for instance from airplanes, birds, or fish The movement of an individual in physical space is therefore mapped as a so-called space-time path within the space-time cube.

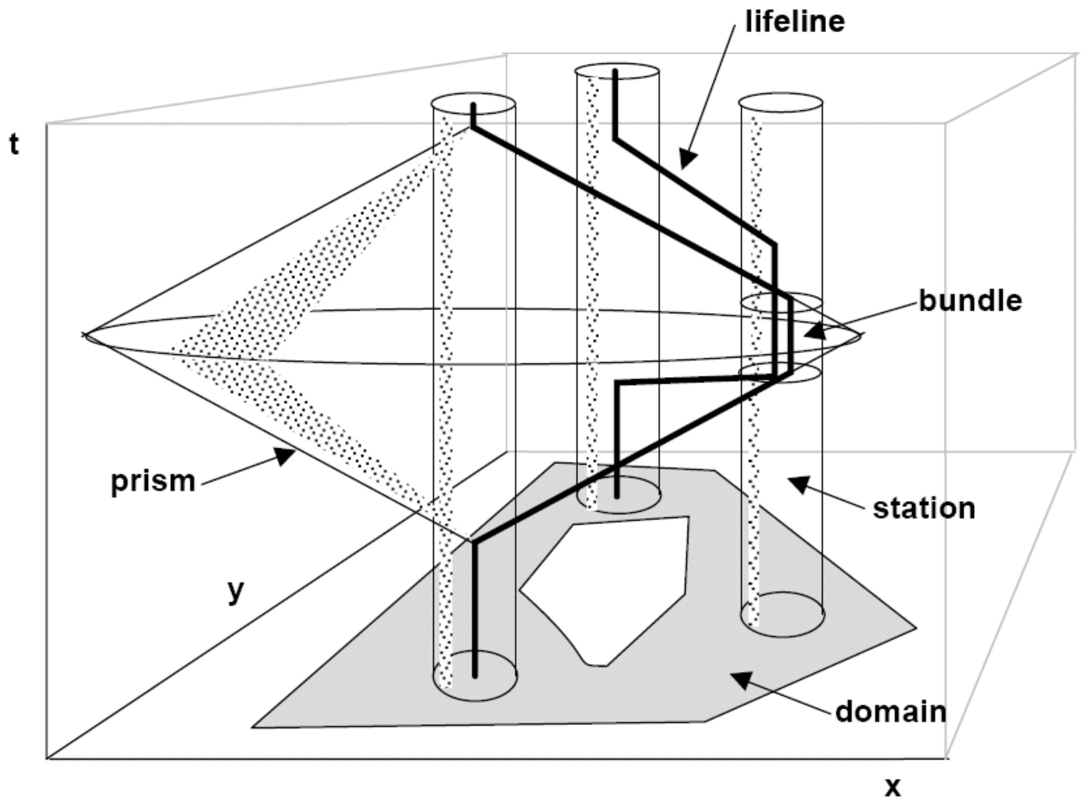


Figure 4: Adoption of the space-time path with a space-time prism (Source: (Moore *et al.* 2003)

The space-time path consists of vertical and tilted segments. The tilted segments represent movement of the object across space and time, while the vertical segments communicate the stationary nature of the object. The degree of tilt corresponds to the speed of the movement. Faster movements have a shallower path, in comparison to steep paths that indicate slower movement.

The concept of the space-time path and its integration into GIS has recently gained renewed interest (Kraak 2003; Kwan 2000; Kwan 2004; Kwan *et al.* 2003; Neutens *et al.* 2008). 3D models and visualizations of human activity patterns have been developed with GIS, in which 3D space-time paths and 2D contextual layers are presented to users for data exploration in 3D. With this method, aggregate and individual activity-travel patterns can be revealed. Yu (2006; 2007) extended this 3D GIS framework for human activities in physical and virtual environments. These authors propose a temporal dynamic segmentation method and four human interaction modes to visually explore traffic congestion, security, and public health issues. Shaw et al. (2008) propose a generalized space-time path approach to visualize spatiotemporal changes among many individuals in large datasets. The authors present a proof-of-concept implementation of a space-time GIS using ESRI's ArcScene and ArcMap modules that provide a respective exploratory spatio-temporal analysis environment to search for hidden movement patterns.

While Hägerstrand developed the space-time model as an analytical tool to study dynamic processes, the time geographic approach in GIS has been more often used to identify and visualize patterns, rather than to explain the process behind the movement pattern. Moreover, the space-time cube often breaks down when large amounts of individual trajectories are depicted in a single display. This is especially problematic, as movement databases are typically massive. The tighter integration of spatio-temporal data into GIS is therefore a great promise, not only to look at patterns, but also to understand dynamic processes.

Studying individual human activity patterns has become a wider research field, perhaps for two reasons: First and foremost, high-resolution data collection has become a rapid and fairly easy process. In fact, large amounts of spatio-temporal data are generated daily through technological devices, such as mobile phones, GPS, and digital navigation aids. Second, advances in computer hardware and software allow for the straightforward processing and interactive manipulation of movement data. Today, activity-based approaches are still used, for instance, for traffic analysis to cope with problems due to managing traffic demand (Axhausen and Gärling 1992), household activity scheduling (Doherty *et al.* 2002), travel behavior (Forer and Huisman 2001), location-based services (Raubal *et al.* 2004), fighting crime (Kapler and Wright 2005), and in general for understanding human migration and mobility behavior (Golledge and Stimson 1997; Miller 1991).

2.2 Data Perspective

While off-the-shelf geographic information systems (GIS) are excellent at representing, and analyzing spatially referenced data, they are still limited in handling temporally referenced, continuously changing spatio-temporal datasets, such as, dynamic patterns, evolving processes, and unfolding events (Peuquet and Kraak 2002). Due to its inherent complex, multidimensional and dynamic nature, the spatial and temporal dimension of geographic data need to be meaningfully integrated into GIS or visual analytics tools for efficient and effective human spatio-temporal information processing and sense-making. In order to make GIS more effective for research in domains that focus on the explanation and prediction of processes and their dynamic patterns, it is crucial to develop new analysis methods that can truly integrate the spatial and temporal components of movement pattern analysis.

Database researchers in the geographic information science and computer science communities have been successful at integrating spatio-temporal data on an advanced database level (Peuquet and Duan 1995), and powerful data-mining techniques have been developed to mine these massive spatio-temporal databases (Miller and Han 2001).

Already in the early 1990s researchers identified the need to include time into geographic information systems to model and represent spatio-temporal processes more effectively (Langran 1992; Peuquet 1994). Peuquet proposes the *Triad Framework* that facilitates the transformation from a "world history model" to a "process model" which reflects a better understanding of the phenomena to be represented (Peuquet 1994). Raper (2000) reflects that new generations of multidimensional geo-representations are key to the process of spatio-temporal reasoning in multidimensional geographic information science. In GIScience several researchers have proposed the integration of time to spatial databases (Grenon and Smith 2004; Hornsby and Egenhofer 2000; Worboys 2005).

More recently, the analysis of moving objects has emerged as a new research thread in geographic information science. Movement patterns can be defined as "any recognizable spatial or temporal regularity or any interesting relationship in a set of movement data" (Dodge *et al.* 2008). The most common representation of moving object data is points, e.g. each GPS fix is represented as one point. Moving objects, according to Dodge et al.

(2008), may be distinguished between geo-referenced and non-geo-referenced moving entities. Geo-referenced objects are moving in physical and human-built landscapes (i.e., humans in cities or animals in their habitats), while non-geo-referenced objects (i.e., avatars in a virtual environment, or gaze points from eye movement data) move in non-geographic space (i.e. virtual environments) (Dodge *et al.* 2008). The most basic conceptualization of a moving object's space-time behavior is a geo-spatial lifeline (Hornsby and Egenhofer 2002), which describes a sequence of visited locations in space, in regular or irregular temporal intervals (Laube *et al.* 2005).

The availability of large movement databases initiates the analysis of more complex questions with the aim to understand movement processes. New approaches are needed to analyze the data and discover movement patterns (Mennis and Guo 2009). In GIScience, Laube et al. (2007b) employ exploratory geographic knowledge discovery (ESDA) that integrates GIS with space-time data mining approaches to reveal interesting spatio-temporal patterns. The *Relative Motion* (REMO) approach (Laube *et al.* 2005), for example, compares motion attributes of groups of moving point objects over space and time and is based on two steps. First, lifeline data is transformed into a REMO matrix, and movements are compared with formalized, generic patterns (Laube *et al.* 2005). Four REMO patterns are introduced and tested in this approach; constancy, concurrence, change, and trendsetter. Laube and Purves (2006) propose to extract movement patterns based on four basic knowledge discovery steps, i.e. data reduction and projection, exploratory analysis and model selection, data mining, and finally visualization. They also propose a method to measure the interestingness of patterns (Laube and Purves 2006) using Monte Carlo simulations, a method that Hägestrand and colleagues pioneered for geography already in the late 1950s (Haggett 2001), specifically for studying movement at a disaggregate levels.

Others have used data mining approaches to identify specific types of movement patterns, such as Andersson et al (Andersson *et al.* 2008) who investigate leadership patterns among spatio-temporal data. Two of the most basic spatio-temporal patterns, namely flock and meeting, are computed with exact and approximation algorithms (Gudmundsson and van Kreveld 2006). Spatial clustering methods are also used for movement trajectory data, for example to identify outliers and path anomalies (Lu *et al.* 2009). Lifeline segmentation and feature extraction methods for revealing physical differences and similarities of moving objects have also been employed (Dodge *et al.* 2009). A general review of existing movement patterns can be found in Dodge et al.

(Dodge *et al.* 2008), who also detail a taxonomy of existing patterns. The identification of movement patterns is a challenge due to the massive volumes and the complexity of spatio-temporal information. Spatial data mining approaches and geographic knowledge discovery are iterative processes that include data selection and preprocessing by computational algorithms, and the evaluation of results to extract useful information from large amounts of movement data (Mennis and Guo 2009).

2.2.1 Limitations of the data perspective

The computational methods reviewed above have mainly focused on the geometrical parameters of movement trajectories and are therefore only describing the characteristics of the movement pattern. These approaches are typically data-driven and do not include respective research goals or tasks of the human analyst, or contextual information, such as the geographic space of the sampled data. I contend that this might greatly hinder understanding the processes underlying these movement patterns. Prior to cell phones and location-aware personal digital assistants, movement data has been collected with detailed travel diaries and activity surveys (Zhao *et al.* 2008). Hence, while the activities and reasons for movement were known (i.e., process), the datasets were tedious to collect and thus often limited in scope and quantity. It seems, however, that quantity is traded for quality today with the automated and fast coordinate recordings through GPS-enabled devices, as research now is attempting to infer the missing semantics from these dynamic moving object data streams. As Zhao et al (2008) rightly note, the human activity that generates movement patterns is not simply an adjunct attribute to a GPS trajectory dataset, but an inherent motivation of the process that generates the movement in the first place (p.199).

With the availability of large amounts of movement data for studying increasingly complex space-time behavior, the presentation, exploration, and analysis of trajectory data have also become cognitively more demanding. Figure 5 shows two movement trajectories from different moving point objects.

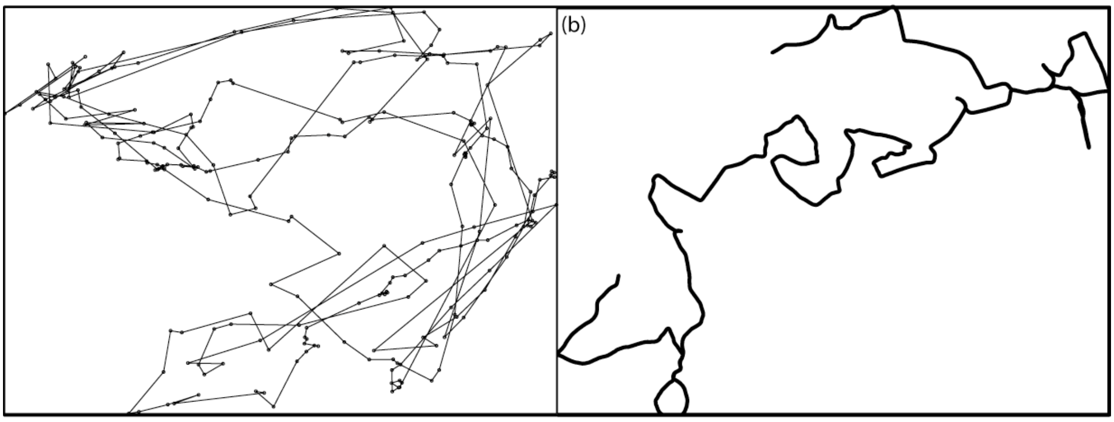


Figure 5: Movement trajectories from two different moving objects

It is clearly visible that the two different types of moving point objects generate different path types. The first trajectory (a) shows a trajectory of a migrating caribou and due to its sampling rate it is presented as a discontinuous path with stop-and-go sequences. In contrast, the second trajectory (b) shows a bicycle rider with a continuous-looking path. The reasons for the different path types are in this case not only the inherent manner of the movement (e.g., differences in speed, velocity, etc.), but also different sampling methods. Hence, domain experts who analyze movement trajectory data have to be aware of the collection details of their data, including the behavioral characteristics of the studied moving objects, i.e. the process that generates the trajectory. Moreover, researchers do not simply use their pattern recognition abilities and discover movement patterns, but do so with a particular research question or discovery task in mind. Additionally, their analysis is based on their previous knowledge of the studied phenomenon (i.e., familiarity with the data), and the scale of the sampled movement data. This simple example suggests that not only geometry plays a major role when analyzing complex environmental processes and spatio-temporal phenomena, but also the semantics, including the context of the moving object (surrounding environment of the object, the influence of other moving objects, spatial and temporal scale of the movement), and the researcher context (task, purpose, cognition, perception).

2.2.2 Proposed avenues

GIScientists have recognized the need for the inclusion of cognitive principles in space-time analysis (Klippel *et al.* 2007; Peuquet and Kraak 2002; Yan *et al.* 2008). Peuquet and Kraak (2002) present a first integration of formal representation approaches with cognitive and philosophical perspectives on space-time to more intuitively handle space-time dynamics in a unified representational framework. Mennis et al. (2000) have made an effort to incorporate cognitive principles into geographic database representations with their pyramid framework. Its core feature is the separation into a data component and a knowledge component. The data component reflects the cognitive process of getting an uninterpreted representation, while the knowledge component reflects the cognitive process that derives knowledge from it and categorizes it.

In 2008, Yan et al. (2008) suggest semantic trajectory modeling in which geometric, geographic, and application domain knowledge is available through ontological modules to improve the understanding of movement trajectories. The semantic information is provided through these ontological models that explicitly model context information of the moving object. The geometric ontology module has information regarding spatio-temporal characteristics of patterns; the geographic module includes concepts about topography, networks, buildings, and places, while the application domain ontology gathers all application dependent concepts, such as traffic management or bird migration. This seems to be a first step to include semantic information of patterns, but needs further investigations for generic, and application-dependent, semi-automatic computation of trajectories (Yan *et al.* 2008). Another way to include semantic information is by modeling events (Hornsby Stewart and Cole 2007; Worboys 2005; Worboys and Hornsby 2004). Hornsby and Egenhofer (2000) address the integration of time into the geospatial domain by modeling specifically the changes of dynamic phenomena. A classic model for the integration of events for spatio-temporal data is Worboy's and Hornsby's geospatial event model (GEM) (Worboys and Hornsby 2004). The GEM adds geospatial objects, events and their settings to existing object-oriented modeling approaches in the geospatial domain and allows queries explicitly related to events. Worboys and Hornsby (2004) demonstrate that this approach leads to more powerful modeling representations of dynamic geospatial phenomena. Ontology-based and event-based approaches are two promising starting points to include the necessary semantics of movement trajectories.

Klippel and other authors are looking at the conceptualizations of events in the geographic domain (Klippel 2009; Klippel and Li 2009; Klippel *et al.* 2010). Klippel et al (2007) identify to what extent formal models of topological relations are able to characterize human concepts of changing relationships between regions. This framework of geographic event conceptualization is formally assessed with empirical experiments where the movement of two regions (visualized by animation) is characterized through a path in a conceptual neighborhood graph. Their results suggest that changes in topological relations are not enough to characterize the cognitive conceptualization of moving regions, and that additional factors are important for the conceptualization of movement, namely the identification of a region, the concept of a region, and the overall dynamics of the involved entities (Klippel *et al.* 2007). In order to extend their findings, Klippel and Li extend this research by investigating, which cognitive invariants are salient in the conceptualizations of movement behavior (Klippel and Li 2009; Klippel *et al.* 2010). The authors present evidence that size matters for the conceptualization of movement patterns (Klippel *et al.* 2010). Their findings are important stepping-stones to identify how events are conceptualized in order to provide a sound theory for analysis of spatio-temporal data. Similarly, the goal of the cognitive conceptual framework is to identify how spatio-temporal data is conceptualized in visualizations of movement.

2.2.3 Summary

In summary, research in movement data storage and analysis has significantly moved forward since the inception of Hägerstrand's time geography. This review has briefly highlighted computer-based exploratory, spatio-temporal data analysis approaches as powerful means to identify changing geometric characteristics of movement patterns, including representations of movement trajectories. However, until now these approaches have only marginally dealt with the semantic aspects of movement information, typically provided by the research goals and tasks, the environmental context, and the human investigating this information. I assume that the analysis of spatio-temporal phenomena cannot be done in an isolated fashion, focusing on the geometrical analysis of patterns alone (Shipley *et al.* 2010), but needs to include the context of the moving object (as described in Section 1.1). The context of the object includes the environment that the objects' movement takes place, the relation to other moving objects, as well as the spatial and temporal scale of the object. All these relations are an important context of the moving object and relations are a focus of human perceptual processes (Shipley *et al.* 2010). I therefore hypothesize that the integration of context facilitates users understanding of movement patterns.

While prior research has made significant advances integrating large, multi-dimensional, spatio-temporal data into query-able databases that can also be explored graphically, movement pattern analysis still seems to rest mainly at the descriptive (i.e., geometric) level. If the ultimate goal of movement analysis is to overcome the gap between pattern and process, the human component needs to be better integrated into the data–system–

human nexus of movement object analysis. The event analysis approach mentioned earlier is a promising start, as events seem to be useful space-time units of human cognitive processing, as we will discuss in a later section on the cognitive perspective. Cognitive principles can also be included into movement data analysis by presenting the results of the computation to a user with meaningful displays. Particularly interactive interfaces facilitate inference and decision-making of the analyst, and leverage the human's outstanding pattern recognition capabilities for analysis. In the next section, I will therefore take a closer look at the visualization perspective, focusing on geovisualization and visual analytics approaches, including respective tools for studying dynamic phenomena.

2.3 Visualization perspective

2.3.1 Revisiting the classics

Dynamic geographic processes, such as movement, have not only gained increasing attention in GIScience, but also in cartography and visualization (Yattaw 1999). Well before the computer age, cartographers have been representing moving objects, such as migration of humans and animals with (static) graphic displays. One common example is the well-known and ubiquitous flow map (Bertin 1983; Tobler 1987). According to Tufte (1983) one of the most compelling space-time stories ever told graphically is Minard's (1869) multivariate flow map of the French army during their Russian campaign 1812-1813. Despite better computing powers, the integration of time into visualizations has become a key challenge (Andrienko *et al.* 2010). Vasiliev (1997) provides a review of spatiotemporal phenomena and the type of representations that have been used so far to represent different categories of time, i.e. moments, duration, structured time, etc.. Taking advantage of computer processing power and interaction mechanisms, Phan et al. (2005) have revisited classic flow maps, and have created interactive flow map layouts with hierarchical clustering techniques. Several Researchers (Hedley *et al.* 1999; Kraak 2003; Kwan 2000; Kwan 2004; Kwan *et al.* 2003) have extended yet another geographic classic—the Hägerstrand space-time prism—to depict travel behavior with 3D space-time paths using the advanced graphics capabilities of GIS. An example is Kwan's space-time aquarium, shown in Figure 6 (Kwan 2004). This space-time aquarium represents individual movement trajectories across space (x-y plane) and time (z-dimension). The biggest advantage of this kind of representation is that time is explicitly modeled through the third dimension, and when viewed in an interactive system, the 3D space can be explored from all angles. However, this representation also has its disadvantages, specifically that large amounts of data can lead to visual clutter and too many trajectories easily overcrowd the representation; an effect which was confirmed in interviews with experts dealing with moving point data. The space-time metaphor breaks down and the movement behavior is difficult to determine.

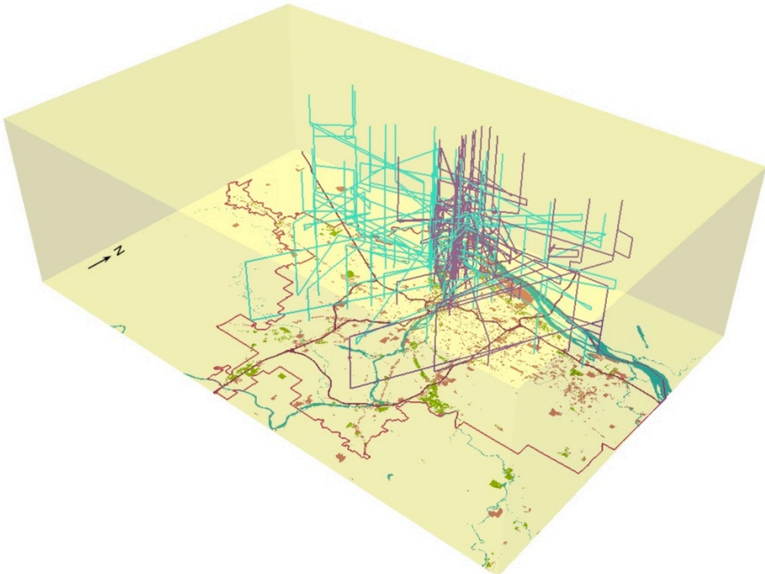


Figure 6: Kwan's space-time aquarium as a 3D GIS visualization method (from Kwan 2004, courtesy to Mei-Po Kwan)

The space-time cube approaches seem to be effective at highlighting similarity in movement trajectories, and thus collective behavioral patterns of individuals (i.e., space-time clustering), but querying and filtering might be better achieved with multiple linked views, for instance by integrating parallel coordinate plots into space-time cubes to allow for interactive exploration of activity travel behavior (Ren and Kwan 2007). It is also common to allow the selection of one time stamp and represent this data item on a map, in a parallel coordinate plot, and a space-time cube at the same time (Blok 2000). In doing so, Ren and Kwan (Ren and Kwan 2007) discovered interactions between movement behavior of humans in the physical and the virtual world.

2.3.2 Explicitly visualizing time

The explicit modeling of time can be done through aggregating the data to observe collective characteristics. Another useful approach is the selection of data (Chen *et al.* 2008), which is often done through multiple linked views in one display. Aigner et al (2008) emphasize not only the importance of choosing visualization techniques according to the data characteristics, but also of the task the analyst has to perform. Aigner et al (2008) differentiate between linear and cyclic time, time points and intervals, and ordered and branching time in their visualization approach, reflecting the space-time characteristics proposed by Vasiliev (Vasiliev 1997). Time series are one of the most common data types (Lin *et al.* 2005) in time-oriented data. Visualizations of time series are approached through timeboxes (Hochheiser and Shneiderman 2001), calendar-based views (van Wijk and van Selow 1999) and spirals (Weber *et al.* 2001) and specifically try to show the time instance when a process or movement has happened. Other approaches for the visualization and discovery of patterns in large time-series data are VizTree (Lin *et al.* 2005) and importance-driven visualizations, in which the user classifies the importance of specific data characteristics, i.e. specific attributes, or time instances (Hao *et al.* 2005). A more detailed summary on these methods can be found in Lin et al. (Lin *et al.* 2005). These highlighted tools have mainly dealt with the explicit integration of time and therefore identify when changes happen in data, but the analysis of movement data deals with the combination of space and time, asking when and where changes of movement behavior are happening.

Important criteria for visualizations of time series data are identified by Aigner et al.(Aigner *et al.* 2008). Important criteria for representations of dynamic phenomenon still have to be found. Even more complex for geovisual analytics is the representation and exploration of time-oriented data and specifically, dynamic phenomena, such as hurricanes, human and animal movement behavior. The sufficient integration of space and time data is therefore a key challenge for visualizations and is so far approached through aggregation, abstraction, and sophisticated computational approaches, such as Self-Organizing Maps (Andrienko *et al.* 2010). At the core of these visualizations lies the interaction with the display that allows the user to explore the data, but it remains to be seen if these approaches are actually cognitively inspiring. The next paragraph therefore deals with approaches that more specifically support users' cognitive abilities.

2.3.3 Using interaction to understand when and where

A step even further towards cognitively supported exploratory visual data analysis are visual analytics approaches (Thomas and Cook 2005). Visual analytics is defined as the science of analytical reasoning facilitated by interactive visual interfaces (Thomas and Cook 2005). According to Keim (2006) the basic idea of visual analytics is to visually represent information, allowing the human to directly interact with it, to gain insight, to draw conclusions, and to ultimately make better decisions. Visual analytics tools typically operate under Shneiderman's visual information seeking mantra, a process of "overview first, zoom and filter, then details-on-demand" to extract relevant information from the data (Shneiderman 1996). Another advantage of visual analytic tools is that they can also be used to display and disseminate findings to a larger audience, e.g., decision-makers and stakeholders.

Geovisual analytics tools have gained increased attention as a complementary method to automated data mining for exploring and analyzing large geographic data sets (Andrienko *et al.* 2008a). Several well-known geovisual analytic tools, such as CommonGIS (Andrienko *et al.* 2007), GeoVISTA Studio (Gahegan 2001) or Improvize (Weaver 2008) have recently been specifically extended to help analysts visually explore and mine very large moving point datasets. Robinson et al. (2005) propose the Exploratory Spatio-Temporal Analysis Toolkit (ESTAT) that combines scatterplots, parallel coordinate plots, bivariate maps, and time-series graphs for a more effective exploration of these large data sets with the contention that multiple visualizations help to extract commonalities and differences among movement patterns. A common characteristic of these highly interactive visualization toolkits is the emphasis of human involvement in the exploration process of spatio-temporal data. The visual inquiry toolkit is based on the previously mentioned visualization mantra of overview first and details on demand, to help users find novel and relevant information by employing both cartographic, and computational methods (Chen *et al.* 2008). These authors (Chen *et al.* 2008) suggest that their pattern basket approach specifically helps users in off-loading cognitive effort, and extending their memory capacity by offering them a digital basket where discovered potentially relevant patterns can be stored during the visual exploration process, and retrieved later, when needed. What is still unclear, however, is whether these approaches indeed facilitate pattern recognition as is commonly claimed (Andrienko *et al.* 2010).

2.3.4 Towards cognitively inspired visualizations

Researchers declared that a better understanding of perceptual-cognitive tasks in the context of visualization has to be attained and supported through empirical evidence (Chen 2005). MacEachren and Kraak (2001) reported that cognitive and usability issues need to be addressed for a systematic improvement of visual analytics tools. This view is supported by Fuhrmann et al. (2005) who conclude that user testing has to be carried out to improve visual analytics tools early on in a user-centered design process, similarly to the design processes in human-computer-interaction research.

Two common visualization approaches are used for the representation of spatio-temporal dynamic data, namely animations and multiple static maps. A current debate focuses on the cognitive issues with these different kinds of representations. The aim is not only to see if visualizations work, but also why they work. Both, static maps and animations have their advantages and disadvantages. Tversky and Bauer Morrison (2002) propose that animations are often too complex and too fast to be accurately perceived. A specific problem is that events and movement are perceived as discrete steps rather than continuous motion, in which an animation does not represent the internal structure of humans (Tversky and Bauer Morrison 2002). In a study on meteorology forecasts Bogacz and Trafton (2005) also observed that participants preferred the static over the animated displays. Lee and Klippel (2005) provide evidence with a similar advantage of static over animated displays and got similar results for display preferences of air traffic controllers. Conversely to these findings, other researchers argue that visual analytics displays should congruently depict the concept of time and change with changing displays over time as with animations (Fabrikant *et al.* 2008b; Shipley *et al.* 2010), as it seems obvious that humans will have less difficulty comprehending complex dynamic processes through well-designed dynamic displays (Tversky and Bauer Morrison 2002). The utility of 2D and 3D displays are equally debated with the goal to understand which representation better fits to the internal representations of spatio-temporal processes (Smallman *et al.* 2001). Another major issue for the exploration and analysis of movement data is the concept of cognitive load. Cognitive load is described as the amount of cognitive resources needed to perform a given task (Wickens and Hollands 1999). Harrower (2007) reviews the cognitive load theory and notes that the effectiveness of a computer interface or visualizations is partly dependent on effectively managing cognitive load. These concepts therefore have to be considered when designing cognitively plausible visualizations of movement. In the next section, I will take a look at research that aims to integrate cognitive principles, especially through the design of event-based visualization approaches.

2.3.5 Using event-based approaches to understand why?

Event-based approaches, as reviewed earlier, also seem to be a promising research avenue to construct cognitively inspired and perceptually salient visual displays for the exploration of spatio-temporal data. GeoTime (Kapler and Wright 2005), for example, visualizes events in a three-dimensional cube, and provides event aggregation techniques to analyze when and where processes occurred. Events are defined by the user and are all actions that can be described, such as "the bear fished at Lake Ontario at 1500 h on July 8th, 2003". The time stamp of the event is safed together with the location information. The user has later the possibility to query the event. In GeoTime the event is visualized through a little pin (see Figure 7), as opposed to non-event based visualizations where only the trajectory would be represented.

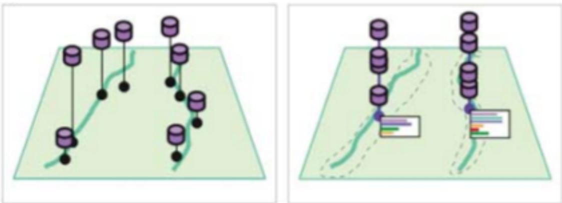


Figure 7: Visualizing events along two routes in GeoTime (Kapler and Wright 2005)by placing pins on top of an event

The EventViewer framework introduced by Beard et al. (2007) supports the user with a combined display, in which users can compare event patterns across space, time, and theme at multiple granularity levels. Aigner et al. (2008) let users define their specific event types, allowing events in the spatial, temporal or attribute dimension. These authors suggest that user centered analysis should be supported through a three-step process in which users specify the event, detect the event, and finally depict the event. These few approaches are promising, because they not only provide user interactivity, but also combine it with human's conceptualization of spatio-temporal processes as successive events. Following Yattaw (1999), the event-based approach seems useful, because it also allows the user to understand the individual spatial and temporal components of each event separately; a pre-exquisite to understanding processes and relationships between movement patterns. Event-based approaches therefore have the potential to understand the actual movement behavior (i.e. process) and not just when and where changes in movement have happened.

2.3.6 Limitations of the visualization perspective

In summarizing previous research within the visualization perspective, I find that many advanced and highly interactive visual analytics tools have been developed to explore and make sense of large space-time data sets. Arguably, geovisual analytics tools have the potential to provide opportunities for spatio-temporal exploratory data analysis, to reveal space-time patterns, and hopefully, to confirm expected, and discover unexpected patterns and relationships buried in massive moving object datasets. The contended advantage of geovisual analytic tools is the combination of computational methods with the outstanding human capabilities for pattern recognition, imagination, association, and analytical reasoning (Andrienko *et al.* 2008b). A survey of the visual analytics literature has shown that mostly the developers themselves use their own tools to explore toy datasets, and to exemplify coded solutions and display characteristics. To the best of my knowledge, there is no empirical evidence that the developed solutions are indeed helping humans (other than the developers themselves) to more efficiently explore large datasets, or to support them in making better decisions. In fact, it is still unclear how these information rich display designs and interactive toolkits effectively combine human's pattern recognition abilities with computational models, and if they support human space-time data exploration, as often claimed (e.g.Beard *et al.* 2007; Fabrikant *et al.* 2008a). Fabrikant and Skupin (2005) contend that visual analytics tools will be more useful if they not only consider how humans perceive and process information, but also augment people's visualization capabilities for complex spatio-temporal reasoning and problem solving.

Understanding perceptual and cognitive tasks in the context of visualization has been under researched so far, and empirical evidence of success is still scarce (Chen 2005) (Fabrikant and Lobben 2009). The congruence principle states that well designed external representations, such as graphic displays, show a natural cognitive correspondence in structure and content with the desired structure and content of the internal (mental) representation (i.e., the appropriate analytical inference). Event-based approaches, as highlighted in the data perspective and the visualization perspective, are possibly one example where the congruence principle works, because events are seen as units that structure our understanding of spatio-temporal processes. In the next section, I present the cognitive perspective, and review relevant work on spatio-temporal reasoning, including event perception and conceptualization that might provide the missing link to prior work in moving object data analysis and visualization.

2.4 Cognitive perspective

In order to understand how humans understand spatio-temporal data and why certain visualizations work better than others, we have to understand how our mind reasons about space and time. One appropriate theoretical construct to study movement behavior from a cognitive perspective is image schemata. Image schemata rely on a small set of experiential concepts and are cognitive structures that help us make sense of our perceptions and actions (Lakoff and Johnson 1980). Image schemas derive from our bodily experiences, e.g., we have to bend down to pick up objects and look up to see the sky, and these bodily experiences reflect in the image schema, in this case "up/down". Lakoff and Johnson (1980) identified eight spatial image schema, e.g. up/down, front/back, left/right, near/far, center/periphery, contact, straight, and verticality, as well as the locomotion schema, e.g., momentum or source/path/goal. Image schema are the source domain for metaphoric mapping, i.e. abstract metaphors that we use in everyday language and thought can be traced back to our conceptual representations, namely image schema (Evans and Green 2006). The conceptual representations of our bodily experiences, i.e. image schema, are reflected in our semantic structure. Language is therefore a conventional mean to understand and decode our conceptual structure. Metaphors are also used to relate to our underlying system of thought. Metaphors are used in language, and are also commonly used to design visual interfaces. Computer file systems, for example, are typically represented metaphorically as an office filing system, containing documents organized in folders. The metaphorical organization of folders and documents relates to the container image schema (Norman 2002).

One important image schema for behavioral movement data is the source-path-goal schema described by Lakoff (1987). Its structural elements are a starting point (source) and endpoint (goal) with a sequence of locations connecting the source and the destination (path) (Lakoff 1987). This image schema is particularly useful for understanding spatio-temporal data, especially movement data, as the visualization of movement trajectories also has a start point, an end point, and change points in-between. Time, as one component of the data, is conceptualized as space - as we will see in the next paragraph - and emerges from our experience with change, which involves motion. Complex events, such as the movement behavior of animals or humans, can be understood with this image schema and thus has been studied with empirical event experiments (Shipley and Maguire 2008). The experiments of this thesis also focus on

how humans understand visualizations of movement trajectories, e.g. assessing the relevance of context to identify certain change points in the movement trajectory, and are particularly relevant to identify useful metaphors for cognitively inspired visualizations.
Reasoning about space and time is also studied from a linguistic point of view. Linguists refer to the fact that we use spatial metaphors when we talk about time, such as "the war is behind us" (Gentner *et al.* 2002). Language often connects space and time by conceptualizing static objects as if they were moving, e.g. the wall runs from the ridge to the valley (Talmy 1983). Casasanto and Boroditsky (2008) examined if the metaphoric use of space for time is not only limited to language or language processing, but also whether it extends beyond the domain of language. Their findings suggest that the relationship between space and time does not only exist in language, but also in our basic representations of distance and duration (Casasanto and Boroditsky 2008). The authors conclude that our mental representations of time may be grounded on our representations of physical experiences in perception and action. Two concepts are differentiated, namely ego-moving and time-moving metaphors, to organize and structure the more abstract domain of time with the more familiar domain of space (Boroditsky 2000; Gentner *et al.* 2002). In analogy to the understanding of a spatial layout through prominent features in the environment (i.e. landmarks), the understanding of the spatio-temporal domain is bounded to events, i.e. prominent features of change. This is comparable to the spatial cognition concepts of allocentric and egocentric frames of reference in the spatial domain. In egocentric frames the spatial information is made in reference to the body and therefore relates to the ego-time concept. Allocentric frames of reference use landmarks, i.e. external frames (Paillard 1991) and can be related to the time-moving concept. These findings present further evidence that events can serve as a cognitively understandable unit and are thus useful in GIS and visual displays of movement. Event points, therefore, have to be made perceptually salient in visual displays of movement, similar to landmarks, as perceptually salient features in the environment. Therefore, I will now review events from a cognitive science perspective and the respective research done on events.

2.4.1 Events from a cognitive science perspective

Shipley and Zacks (2008) demonstrate that events are things that happen with a reference to a location in time. Several authors (e.g.Kurby and Zacks 2008; Zacks and Tversky 2001) define an event as "a segment of time at a given location that is conceived by an observer to have a beginning and an end". Events are mental units and are considered as our building blocks of the temporal realm (Schwan and Garsoffky 2008; Shipley 2008). Although events are seen as units, analogies can be drawn between events and objects (Casati and Varzi 2008; Schwartz 2008; Shipley 2008; Shipley and Maguire 2008). While objects belong to the spatial dimension without a temporal frame of reference, events are set in the temporal dimension (Casati and Varzi 2008; Shipley 2008; Tversky *et al.* 2008) and occur when objects change or interact (Shipley 2008). Although events are defined through their temporal dimension, they do have a spatial dimension as well. This means they can change their spatio-temporal position (Tversky *et al.* 2008) and allow a co-location in space (Casati and Varzi 2008).

Event segmentation is an important process that helps humans to partition and store events in cognitively manageable units (Kurby and Zacks 2008; Schwan and Garsoffky 2008). Segmentation features can be the change of location (Schwan and Garsoffky 2008), or movement changes including the acceleration of objects (Tversky *et al.* 2008). Event segmentation is influenced by goal-directedness (Schwan and Garsoffky 2008; Zacks 2004), or familiarity (Schwan and Garsoffky 2008). Several authors suggest that event segmentation is influenced by cognitive top-down processes, such as knowledge of goals and causes, as well as bottom-up processes that are perceptual (Tversky *et al.* 2008; Zacks 2004).

The boundary of an event is the most crucial part of an event because it contains the most important information (Schwan and Garsoffky 2008; Shipley 2008). Chelappa et al. (2008) mention that abrupt changes in the transformation of objects should be associated with boundaries of events. Directly related to the development of visualizations of spatio-temporal data (and ultimately also our framework) is that experiments has been conducted with the goal to identify potential perception features of event boundaries by focusing on the motion of individual objects in space (Shipley and Maguire 2008; Tversky *et al.* 2008; Zacks 2004). These authors used an objects' movement path for several reasons: First of all, the concept of path is fundamental to event classification in language. Secondly, mathematical tools are available for characterizing paths, and thirdly, path features are most likely used by observers to segment movement events (Shipley and Maguire 2008). Moreover, empirical research has been established to understand if object and event segmentations relate, and a high correlation was found between object and event boundaries (Shipley and Maguire 2008). A detailed review on events from a visual perception perspective is found in Shipley and Zacks (2008). It includes the development of event understanding, perceiving and segmenting events, as well as the internal representation and memory of events.

The segmentation process is typically measured through the setting of perceptual and cognitive breakpoints, i.e. where and when humans perceive the boundary of an event (Newtson 1973; Newtson and Engquist 1976; Schwan and Garsoffky 2008; Tversky *et al.* 2008) by segmenting movies. Here again, the process of event segmentation is comparable to the process of object segmentation. While visual processes focus on the boundary of objects, Shipley (2008) focuses on the temporal regions near the points of change for events. Event segmentation can be less or more fine-grained, where a more fine-grained segmentation indicates a higher density of event boundaries and therefore a higher amount of extracted information (Schwan and Garsoffky 2008). Events can also be subdivided into meaningful units, creating events and subevents (Kurby and Zacks 2008). A more detailed review on human segmentation process of events can be found in Kurby and Zacks (2008).

Although events and objects are clearly different, the possibility to draw analogies from events to objects leads to the potential to model and analyze events with GISystems. It is specifically important to note that the Zacks and Tversky (2001) conclude that the spatial and the temporal component complement each other when reasoning about events. Consequently, it suggests that the usage of event-approaches in the data and visualization component is potentially valuable, as we will see in the summary of this section.

2.5 Summary

The cross-disciplinary review of previous work on moving object data storage, representation, analysis and visualization suggests that only a weak link exists to current cognitive and perceptual research that can be integrated into current visual-analytic approaches to better explore and make sense of large amounts of movement data. This might not only hinder significant advances in this emerging research field, but also seems particularly problematic when trying to explain and predict behavioral movement patterns. Ideally, movement behavior and its analysis are understood as a cycle. Figure 8 represents this cycle. Movement behavior can be measured and captured in data for analysis, which in turn is presented to analysts through visualizations of movement. These visualizations should be depicted such as to facilitate cognition and perception of the pattern, allowing the analyst to identify patterns of movement behavior.

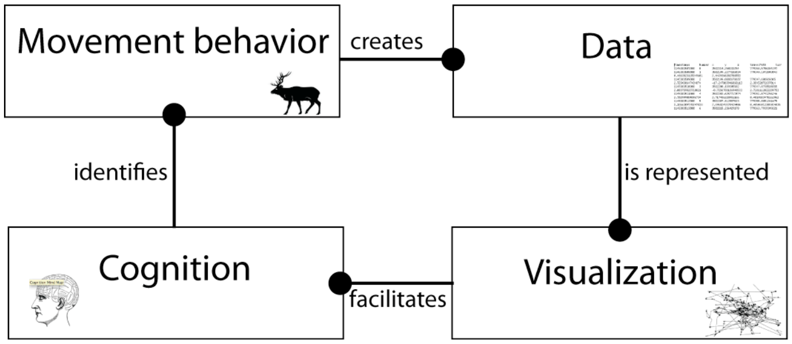


Figure 8: Ideal cycle of movement behavior and its analysis

I claim that visualizations of movement behavior are not yet established in a cognitively inspired way, as the link between visualizations and human perception and cognition is still weakly defined. I therefore propose a cognitive conceptual approach for movement representations and depictions that includes empirically validated knowledge on how humans perceive and understand movement behavior depicted in visual analytics displays. Chapter 3 details the conceptual framework of movement and explains why human subject experiments are a suitable method for identifying how humans conceptualize spatio-temporal patterns.

3. A cognitive conceptual framework for movement data visualizations

The proposed conceptual framework aims at improving visualizations of moving point data for more effective and efficient exploration and decision-making. It is specifically strengthening the weak link between cognition and perception and visual displays (compare with Figure 9). Various researchers have already suggested that an appropriate starting point for constructing effective and efficient visual analytics tools is to frame developments within context of cognitive theories, long-standing empirically evaluated design principles, and related empirical studies on visual displays (Fabrikant and Lobben 2009; Slocum *et al.* 2001). As introduced earlier, I propose three pillars for our framework on moving object research linking collected movement data (i.e., data perspective) with human inference and decision making (cognitive perspective) through cognitively inspired visual analytics displays (visualization perspective), see Figure 9. All perspectives have top-down and bottom-up components. The top-down components include theories and principles from existing research. The bottom-up components consist of user-oriented approaches.

The taxonomy of movement patterns is to date one of the main contributions of the bottom-up perspective of the data perspective. The cognitive perspective is dominated by human subject experiments, such as the assessment of the influence of a moving objects' context, or the context of the analyst. The cognitive perspective links the data and the visualization perspective to show that the user has to be supported by cognitively inspired visualizations. Visualizations are not alone determined by their data structure, but rather progress through a filter with cognitive aspects. The visualization perspective is characterized through the design and evaluation of visualizations of movement. The visualization perspective also has a backward link to the cognitive perspective, which symbolizes that designing cognitively inspired visualizations of movement is an iterative process, and new findings from cognitive research have to be assessed and integrated continuously.

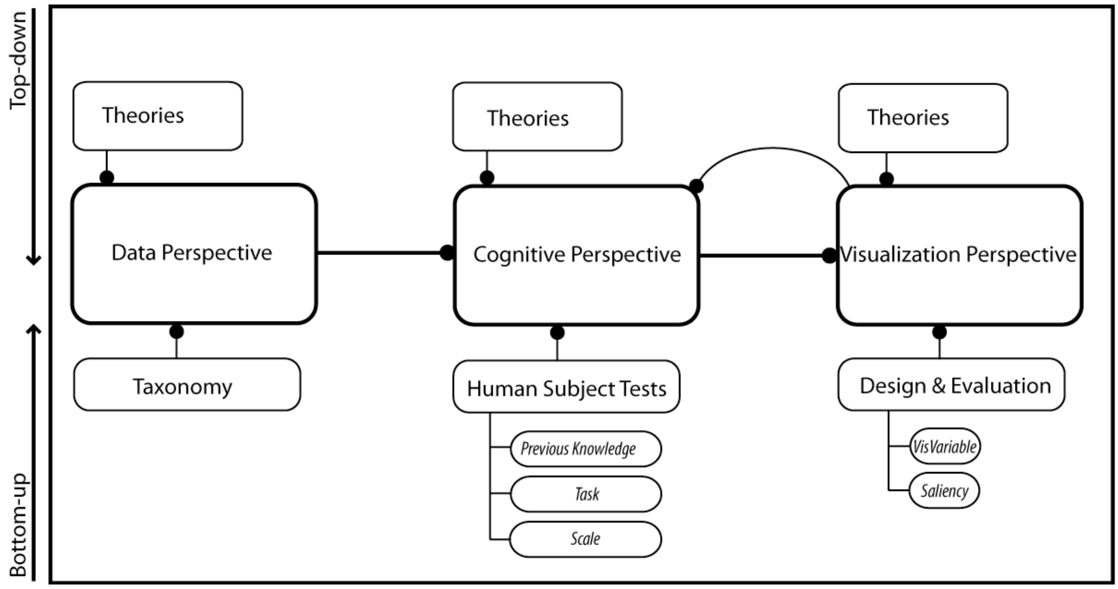


Figure 9: A cognitive conceptual framework for movement visualizations

3.1 Data perspective

A movement pattern can be made of a single, basic movement parameter, e.g. change of direction, or combinations of movement parameters, e.g. change of direction and change of speed. Certain combinations of generic parameters of movement data (i.e. distance, direction, speed, velocity, position, interval, and distance) form a movement pattern (Dodge *et al.* 2008). Such patterns can be organized in a taxonomy of movement patterns as shown in Figure 10 (Dodge *et al.* 2008)[1]. The taxonomy distinguishes generic and behavioral movement patterns. Generic movement patterns may be found in any form of movement from any kind of moving object, such as animals or avatars. Generic movement patterns can be classified on different levels of complexity, namely primitive and compound patterns, as shown in Figure 10. Primitive patterns involve only one moving object (e.g. incidents and constancy), while compound patterns are made up of several moving entities and their inter-object relations (e.g. trend-setting, encounter). In contrast, behavioral patterns explain the specific behavior of particular moving objects.

1 available online as to invite researchers to contribute to the evolving taxonomy:
http://movementpatterns.pbworks.com/Patterns-of-Movement

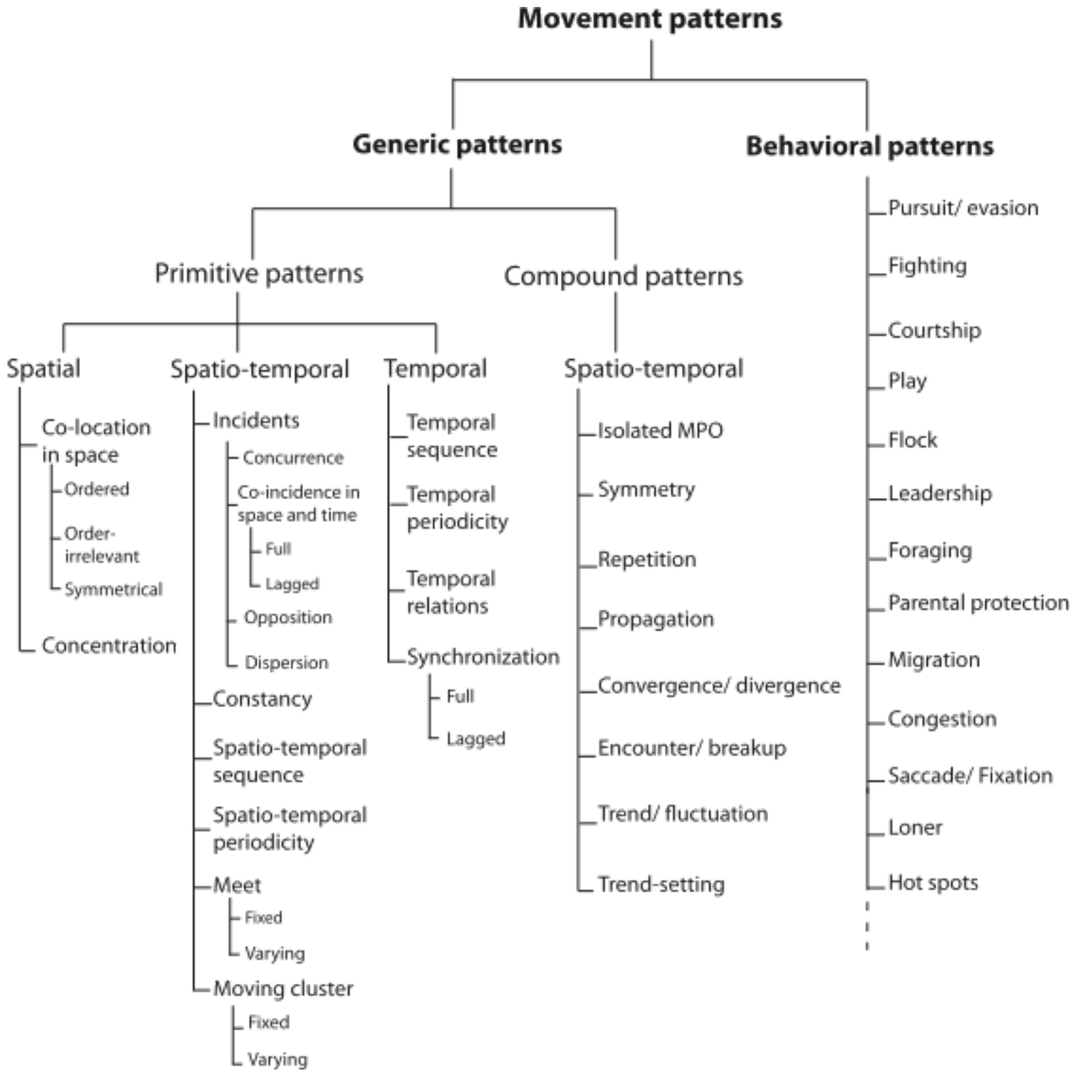


Figure 10: Taxonomy of movement patterns (Source: Dodge, Weibel, Lautenschütz, 2009)

Since all movement patterns are generated through behavior, the term *behavioral patterns* (as opposed to generic patterns) is not ideally coined by Dodge et al. (2009). It would be better to use the term *semantic patterns* to reflect that these patterns are not just a mere combination of movement parameters, but that these patterns have *meaning* as they are only applicable to a particular behavior of a particular moving object. Semantic patterns are therefore dependent on the context of the moving object. In the remainder of the thesis I keep the term behavioral patterns though to avoid confusion, although I think semantic pattern would be more suitable.

As discussed in Chapter 2, a lot of research is dedicated to formalize generic movement patterns. Expressed formally, Laube et al. (2005) propose that a movement pattern P describes a sequence (S) of motion attributes (A_m) over time (1). A pattern P at a particular instance of time describes an incident I of a set of motion attributes (A_m) in time (2).

$$P=S(A_{\mathrm{m}}) \qquad (1)$$
$$P=I(A_{\mathrm{m}}) \qquad (2)$$

Collected movement data can be structured and stored as proposed, but the question remains how people perceive and understand data patterns, i.e., stored in a database, or visualized in a display, and what resulting spatio-temporal inferences users can make from these patterns (i.e., see cognitive perspective in Figure 9). Following a psycho-physical framework (Stevens 1957), the pattern P in a stimulus-response relationship (3), is described by the following psychophysical function:

$$P_{\text{data stimulus}}=kP_{\text{human response}}^{(n)} \qquad (3)$$

From this formula follows, that only if the exponent (*n*) equals 1, an existing pattern (P) (including a constant *k*) is indeed perceived as the data pattern without information loss or distortions of any sort. Considering previous research on event perception and understanding, we contend that cognitively inspired visual analytics displays are necessary to minimize potential information loss, as they aim at supporting effective and efficient pattern perception and pattern recognition. The effectiveness and efficiency of a visual display is dependent on various human centered aspects, such as users' individual differences (e.g., spatial visualization skills, visual acuity, etc.), previous knowledge and training, usage contexts including tasks and goals, and the visual characteristics of the display themselves. I therefore propose that cognitively inspired representations of movement data also integrate a perception and cognition component into the basic ontological pattern functions described in the taxonomy of movement patterns (Dodge *et al.* 2008). A movement visualization V_m therefore includes a cognition *C*, perception (P_e), and pattern (P_a) component as shown in (4):

$$V_m=CP_{\mathrm{e}} + P_{\mathrm{a}} \qquad (4)$$

The taxonomy of movement patterns reflects that researchers have mainly worked on various generic movement parameters (i.e., position, distance, direction, etc.) of the pattern function (P_a) (Dodge *et al.* 2008). In contrast, the behavioral patterns have not received much attention and have not been formalized in detail yet. Especially semantic aspects, such as the context of the moving object (i.e. goal and task directed movement, influence of other moving objects), or characteristics of the moving agent (e.g., modality of movement, etc.) have not been considered yet. Furthermore, the cognitive and perceptual aspects of the researcher trying to make sense of the resulting pattern have also hardly been researched. From this follows my approach to identify the various components influencing the cognition component *C* (in 4).

3.2 Cognitive Perspective

In order to get a more in-depth understanding of the potential factors that could be most relevant for the analysis of spatio-temporal data (and thus need to be captured in the cognitive function), we need to specifically address the user working with movement data (see center part of Figure 9). The top-down knowledge of the cognitive perspective are existing theories and principles from cognitive science, and this thesis specifically draws on existing research on events and event segmentation. This dissertation tries to contribute to the bottom-up approach of the cognitive perspective by using qualitative interviews, controlled human subject experiments, and eye movement research.

The key objective of the cognitive perspective is to develop a sound theoretical foundation based on empirical evidence how humans process spatio-temporal information in visual displays of movement, and thus getting an understanding on how humans understand the complex and multidimensional nature of the data. From expert interviews (described more detailed in Chapter 4.1), we identified three major candidates for the cognition component in Equation (4), namely, previous knowledge (familiarity), training, task (goal-directedness), and scale that guide the analysis of movement data beyond geometric parameters. These factors also correspond well with the factors cognitive research has shown to influence human event segmentation (Schwan and Garsoffky 2008; Zacks 2004), as reviewed above. Previous knowledge has been the major driving force to analyze movement patterns for the interviewees and is part of the analysts' context. One important factor to assess is how the analysts' context, such as their previous knowledge, is influenced by the visual representation of the moving object's context, e.g. the environment in which the movement takes place. Context information is therefore a key concept, which helps users to add meaning to data and visualizations. The interviews have highlighted the importance of context information about the moving object, but I briefly state two other reasons, why context should be considered in our empirical investigations.

Literature from context-awareness research also emphasizes the importance of including "relevant information for the user" (Dey and Abowd 2000), which is in turn dependent on the users geographic context. The issue of context-awareness has been well recognized in computer science, especially for mobile applications (Dey and Abowd 2000; Schilit *et al.* 1994; Schmidt *et al.* 1999). In mobile computing, a system is context-aware if "it uses context to provide relevant information and/or services to the user, where relevance depends on the users task" (Dey and Abowd 2000). This statement should not only be essential for mobile application, but also to visual analytics applications. However, context awareness is so far lacking in the design of visual analytics tools, in particular for space-time data.

Another reason why I considered context as an important factor is the differentiation of generic and behavioral movement patterns in the taxonomy of movement patterns. Generic movement patterns rely on the identification of basic, generic movement parameters alone. Movement parameters can answer questions where changes in movement trajectories from moving objects have happened, what kind of change has happened in the trajectory, and when changes in the trajectories of moving objects have happened. The questions where, when, and what therefore only correspond to the movement trajectory, and not to the actual geographic location of an object. In contrast, behavioral movement patterns additionally need context information to the basic movement parameters to employ meaning to the represented movement patterns (see Figure 11) and to specifically answer why movement behavior is happening.

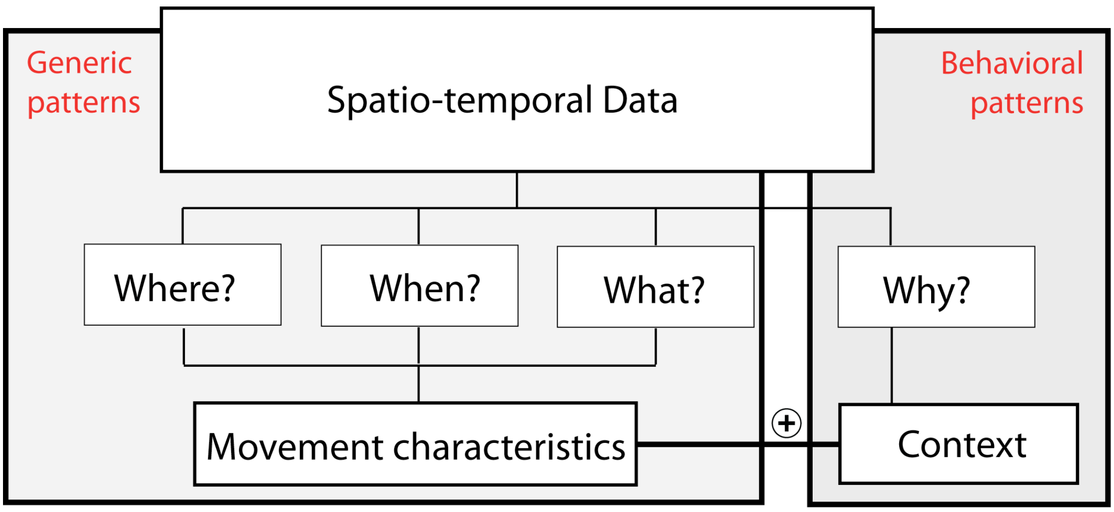


Figure 11: The identification of generic and behavioral movement patterns

Consequently, I have first given attention and initially manipulated visual representations of the moving objects' context in my human subject experiments (Lautenschütz 2009; Lautenschütz 2010), to demonstrate the importance of contextual information about the moving object in visual displays of movement patterns (as mentioned in Chapter 1.2). Throughout this thesis, I am therefore testing the two following hypotheses statements (HS_1 and HS_2):

> *HS_1: Generic movement patterns can be identified through the identification of basic movement parameters, such as speed, distance, direction, and velocity and need no context information of the moving object to understand what movement pattern is visible.*

> *HS_2: Users need context information of the moving object to correctly identify behavioral patterns and understand why the movement has happened.*

Two definitions are used throughout the experiments to manipulate context information in the visual displays. The first experiment is inspired by context-awareness literature, where context is defined as "relevant information" (as described above). I consider relevant information of the object as information regarding the kind of moving object, i.e. humans, and the object's behavior, i.e. bike movements. In the second and third experiment, I defined context as the environment in which the movement takes place, i.e. the geographic context of the moving object, such as high alpine terrain for ibex. The experiments are guided by the following overall research question, as mentioned in Chapter 1.2:

> *What is the effect of context information on the exploration and analysis of movement data?*

More specifically this research question is split into two objectives: The first objective aims at identifying if context information of the moving object influences the identification of the moving agent and the designated movement behavior. The second object aims at identifying to what extent context information of the moving object influences the identification of basic movement parameters, e.g. speed, velocity, or duration.

Once we have identified the key components of humans' understanding of movement and events, we are better equipped to match the external visual representations, i.e., cognitively inspired visual analytics displays of movement data to the internal (mental) representations of humans. The derived knowledge from user testing could then be integrated into the design process of generating effective and efficient visual analytics displays of movement data, which in turn will enable humans to make better spatio-temporal decisions.

3.3 Visualization perspective

The visualization perspective (right part in Figure 9) depends on long-standing design principles and practice, as well as additional information from ongoing and future empirical evaluations. Certainly a good start for constructing effective and efficient visual analytics displays are the design principles and details on how to transform spatio-temporal data into visuo-spatial forms, outlined in various standard cartography text books (e.g.Slocum 1998). Bertin's (1983) system of visual variables, and later extensions into the dynamic domain by DiBiase et al. (DiBiase *et al.* 1992), are prime candidates also for movement visualizations.

We have seen earlier that debates still exist on the adequacy of certain representation types for (movement) visualization, i.e., with respect to the appropriate dimensionality (2D or 3D) and/or the level of inclusion of dynamics (i.e., animation, interaction, etc.).

The framework therefore has to carefully consider appropriate design principles, also supported by empirical evidence, to show a coherent representation of movement. The appropriate selection of the visual variables for movement displays is also crucial, as some variables are perceptually more salient than others (Garlandini 2009; Garlandini and Fabrikant 2009). In cognitively inspired visualizations, thematically relevant information should be rendered perceptually most salient for effective and efficient spatio-temporal inference and decision-making (Fabrikant *et al.* 2010).

Current state-of-the-art movement pattern research, as we have seen earlier, focuses mostly on the automated analysis of geometric properties and features, and the extraction of movement patterns by means of algorithms (Dodge *et al.* 2009; Laube *et al.* 2007a). However, we do not know whether the geometric properties extracted by algorithms match humans' internal representations of movement and adequately capture the semantics of the movement behavior. For example, my interviews with experts suggest that the inclusion of contextual information is especially critical for the analysis of behavioral movement patterns. Visualizations of movement data should therefore not only focus on geometric properties (i.e., paths and configurations), but also include adequate depiction of context information (i.e., environment, goals, tasks, spatio-temporal scale, etc.). Event-based approaches, as highlighted earlier, would be a good starting point. In order to match human's conceptualization of events, event points should be made perceptually salient, similar to landmarks as salient features in the environment.

4. Methodological Overview

The conceptual framework, as discussed in the previous section, consists of a top-down perspective, i.e. existing theories and principles, and a bottom-up perspective, e.g. empirical investigations. In this chapter, I discuss the contributions to the bottom-up perspective within the cognitive perspective of the conceptual framework by using qualitative interviews, and controlled human subject experiments employing eye movement research. This chapter introduces the methods used throughout this thesis.

4.1 Introduction to empirical investigations

A systematic empirical evaluation on how context influences inference and decision-making with visual analytics displays is a key requirement for the development of cognitively inspired visual analytics tools. The effectiveness and efficiency of visual analytics tools has gained recent interest in GIScience (Cöltekin *et al.* 2010; Cöltekin *et al.* 2009; Fabrikant *et al.* 2008a; Fuhrmann *et al.* 2005; Li *et al.* 2010). Demsar (2007) developed a methodology to perform usability evaluation with visual analytics tools as a key step to improve visual analytics tools. Other empirical studies investigate with the effectiveness of visualizations when visual variables are manipulated (Fabrikant *et al.* 2010) as a key factor for cognitively inspiring visualizations. The exploration of spatio-temporal data, specifically movement, with visual analytics tools has rarely been empirically assessed. Human subject experiments provide a direct window to the users experience and decision-making with visual analytics tools and visualizations of spatio-temporal data. I argue that human subject testing is necessary to support the development of visually inspired geovisualizations for effective and efficient exploration of movement data.

The literature review has shown that the analysis of movement patterns has often focused on the identification of geometric parameters, such as change of speed or change of direction. Hardly any attention has been given to the semantics of movement patterns, such as the kind of moving object and its geographic context (also see (Klippel *et al.* 2010), p.132). This empirical part of this research aims at providing insights to the existing body of knowledge on how users conceptualize spatio-temporal data and how context information helps to identify movement patterns. Only a few empirical studies have examined how humans conceptualize spatio-temporal data (Klippel 2009; Klippel *et* *al.* 2010) so far. It is unclear at this point how context might influence the identification of behavioral movement patterns. This series of experiments also aims at identifying how users conceptualize spatio-temporal data, particularly individual movement behavior, but in static 2D representations. .

4.2 Methods used

I approach this interdisciplinary research question with a series of complementary empirical methods that are described in the next section, such as qualitative interviews and controlled experiments.

4.2.1 Qualitative Interviews

Semi-structured qualitative interviews were conducted at the beginning of the project to identify potential factors that could be most relevant for the analysis of spatio-temporal data. These interviews were carried out with four experts using movement data in their daily research work. I recruited three moving data experts from zoology, anthropology, and transport planning at the University of Zurich and the ETH Zurich. The fourth interviewee is an air traffic controller at Zurich International Airport. The interviews consisted of three parts. The first part aims at understanding what kind of movement data participants typically use in their research context. Insight is gained in goal and task-dependent information that participants might be looking for in movement data (e.g. location information for home ranges in ecology), and also to what extent participants have experience with visualizations of movement. In the second part of the interview participants are shown four different displays of a single movement trajectory without any additional metadata, or spatial, or temporal information (see Figure 12).

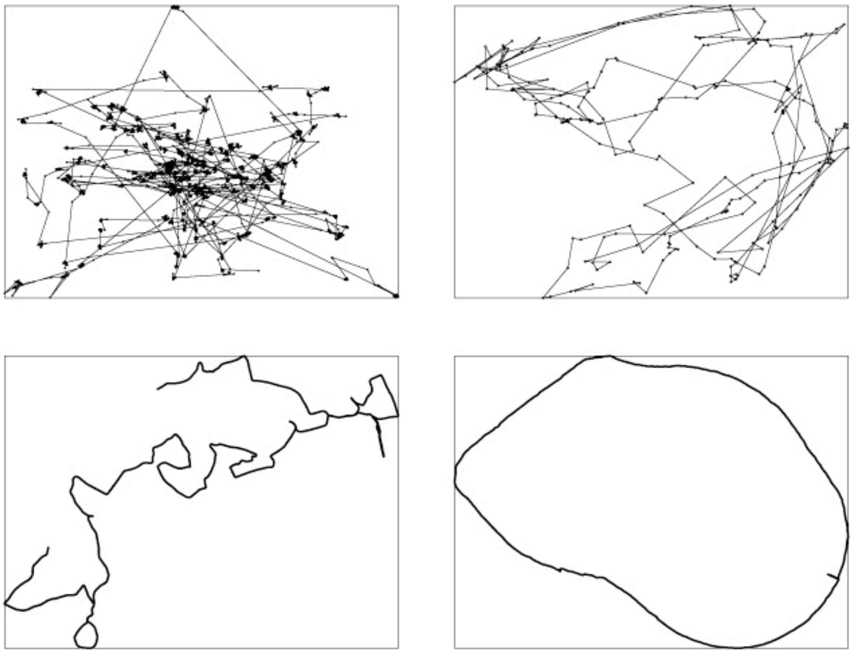


Figure 12: Movement trajectory displays shown to interview partners

The objective of this part of the evaluation was to identify how participants explore spatio-temporal trajectory data, which strategies they intuitively adopt to understand the data, and whether their own research context drives the analysis. The participants were asked to think aloud while exploring the various shown trajectories, to express what they thought to recognize in the displays, and what kind of moving objects created these trajectories. Participants were then asked to rank how important they considered the following aspects: their own background knowledge, additional information about the object, and spatial and temporal scale of the object for the analysis of spatio-temporal data in visualizations. Results of these interviews suggest that previous knowledge of the analyst, domain specific tasks, as well as context information about the object, and spatial and temporal scale of the object, influence the identification of movement parameters. In the third part of the interview, participants were shown three different, commonly used visualizations of movement data, typically found in the current literature, such as the space time aquarium from Kwan (Kwan 2000)(see Figure 6). They were asked to assess the utility of the visualizations to recognize the behavior of moving objects and to identify patterns. Since the participants have had varying experience with visualizations of movement data, the preferences and perceived utility of the visualizations were also quite varied. Participants had difficulty to analyze or to understand visualized trajectories that did not fit the expected behavior of their assumed moving object. Therein lies an important component of the proposed cognition function (see Chapter 3), requiring more research attention. Especially the three dimensional depiction shown (from Kwan, 2000; see Chapter 2, Figure 6) proved to be very difficult to understand for half of the participants. All participants made recommendations and suggestions for improving the shown visualizations. The interviews revealed that researchers automatically adopt their usual inference strategies as if they were working with their own data, even when analyzing unknown data. They also seemed to have difficulties understanding displays of movement data they had never seen before, such as the classic space-time cube.

4.2.2 Controlled Experiments

Controlled experiments allow the precise manipulation of a condition, to be able to measure the behavior of participants (Martin 2008). All of the experiments are controlled experiments, because in each case I tested context through graphically manipulated stimuli. The advantage of this method is that precise measurements are possible to test if the response behavior of the participants changes, depending on the visual input we provide them with. One of the disadvantages of this method is that the setting is artificial, i.e. participants had to come to our lab and do the respective tasks (except for the online experiment described later). Therefore also the intrusiveness is fairly high, because participants are not using visual displays of movement in their own research context, but have to perform a predefined task. However, it allows a researcher to draw causal conclusions between test conditions and participants' answers and thus test our hypothesis that context matters for the identification of moving object and its behavior.

Eye movement research is considered an additional approach to complement traditional performance measures (Li *et al.* 2010) and is briefly introduced now, as it has been employed in my first experiment. Recent software developments allow the easier collection and analysis of eye movement data (Li *et al.* 2010). It has therefore become more attractive recently to employ eye movement analysis not only in human computer interaction research or for studying cognitive processes, but also in the geovisualization domain (Cöltekin *et al.* 2009; Fabrikant *et al.* 2008a; Fuhrmann *et al.* 2005; Haklay and Zafiri 2008). Eye movement recordings are arguable considered as an objective measure to understand cognitive processes involved when people are presented with complex displays of spatio-temporal data. Eye movements consist of saccades and fixations; saccades being fast, uncontrollable "jumps" from one fixation to the next fixations. Popular efficiency metrics are fixation duration and time to first fixation in areas of interest (AOI) analysis to identify which part of the visualization attracts attention, and where people are looking to solve specific tasks. These metrics are typically represented in density maps, gaze plots or graphs. We have used eye movement research in our first experiment to get a more in-depth understanding where participants are looking to solve various tasks, thus being able to identify more clearly if and when context information seems relevant. This controlled experiment was conducted in our eye movement lab at the University of Zurich in individual participant sessions.

I have used an online experiment for our second experiment, using open and closed questions. Web-based questionnaires have the advantage that the data collection is fast and efficient, although response rates are lower when used as an online questionnaire. The data from online experiments allows a fast measurement of opinions and attitudes. A disadvantage is that answers to open questions by participants are hard to verify (Martin 2008). The closed questions of this experiment were statistically evaluated, while open questions could just provide trends.

5. Empirical Evaluations

5.1 Experiment I – relevant information

This first experiment assesses the influence of context information on the exploration and knowledge extraction from static, 2D trajectories of moving point data, i.e. human movement data. One kind of context information is the kind of moving object and its behavior, i.e. the intrinsic pattern characteristics. Extrinsic characteristics of patterns are the surrounding environment, the influence of other agents, as well as spatial constraints, such as networks and barriers (Dodge *et al.* 2008).

At least seven spatial, temporal, and spatio-temporal parameters can be extracted from a movement trajectory, and are the basic primitives of individual movement, as identified in the taxonomy paper (Dodge *et al.* 2008). These parameters are position, distance, direction (spatial characteristics), instance, interval (temporal characteristics), as well as speed, and velocity (spatio-temporal characteristics). The basic movement parameters, as well as the intrinsic pattern properties, are the first parameters of movement behavior to be assessed in an empirical investigation. In this first experiment, I define context as "additional relevant information". Context is graphically manipulated by adding a legend and a title to the movement trajectory, thus revealing the object and its behavior (i.e. bike movement of an individual in one day). The experiment aims at answering the following two research questions:

> **Q1a:** Does additional contextual information, provided in the form of legend and title, help participants to identify a moving object and its behavior?

The experiment has two parts. In the first part participants are asked to identify an object and its behavior based on a single movement trajectory. The second part of the experiment looks at the intrinsic pattern characteristics and analyses whether participants' are able to identify the movement parameters correctly. It tries to answer the following question:

> **Q1b:** Does context information help for the identification of basic movement variables, such as distance, duration, speed, velocity, and position?

I chose two spatial parameters (position, distance), one temporal parameter (duration), and two spatio-temporal parameters (speed and velocity) for the empirical assessment. Velocity is defined in these experiments as the change of speed in a movement, i.e. the acceleration over a (short) period of time, while speed looks at the specific speed at a certain point in time. The movement parameters were used to assess user's performance (i.e. response accuracy) and efficiency (i.e. response time) when identifying movement parameters.

5.1.1 Participants

Fifty-one participants took part in the experiment in our eye movement lab at the University of Zurich and additionally 15 subjects participated by online questionnaire. All participants were mother tongue German, as this was a requirement to be able to participate. A 53% of the participants are male and 47% are female. Hardly any of the participants is familiar with the analysis of movement data (1.5%) as well as with software to analyze movement data (1.5%). A majority of the participants is between 20-30 years of age (57.6%), or between 31-40 years (39.4%). These numbers are not a surprise as the majority of the participants were researchers and students from the Department of Geography at the University of Zurich. They received a coffee voucher for the campus cafeteria in return for their participation.

5.1.2 Experimental Design

The independent variable in this experiment is context. The measured dependent variables are the effectiveness (i.e. response accuracy) of identifying a movement characteristic and the efficiency (i.e. response time) of the participants measured in response time. Context information was manipulated with three graphical conditions in a between-subject design. The first display shows a movement trajectory without any additional information. The second stimulus includes spatial and temporal information in a legend (i.e. a scale and the temporal resolution), additional to the movement trajectory. Even more information is provided in a third stimulus, by adding a meaningful title revealing the kind of moving object and the movement activity shown in the trajectory. Figure 13 shows the three conditions for the first part of the analysis, where users are presented with a full trajectory. The experiment had a between-subject design to avoid potential learning effects. Each group of participants was only exposed to one type of stimulus and therefore only to one level of the independent variable, namely (a) without context information, (b) with a legend, or (c) with a title and a legend.

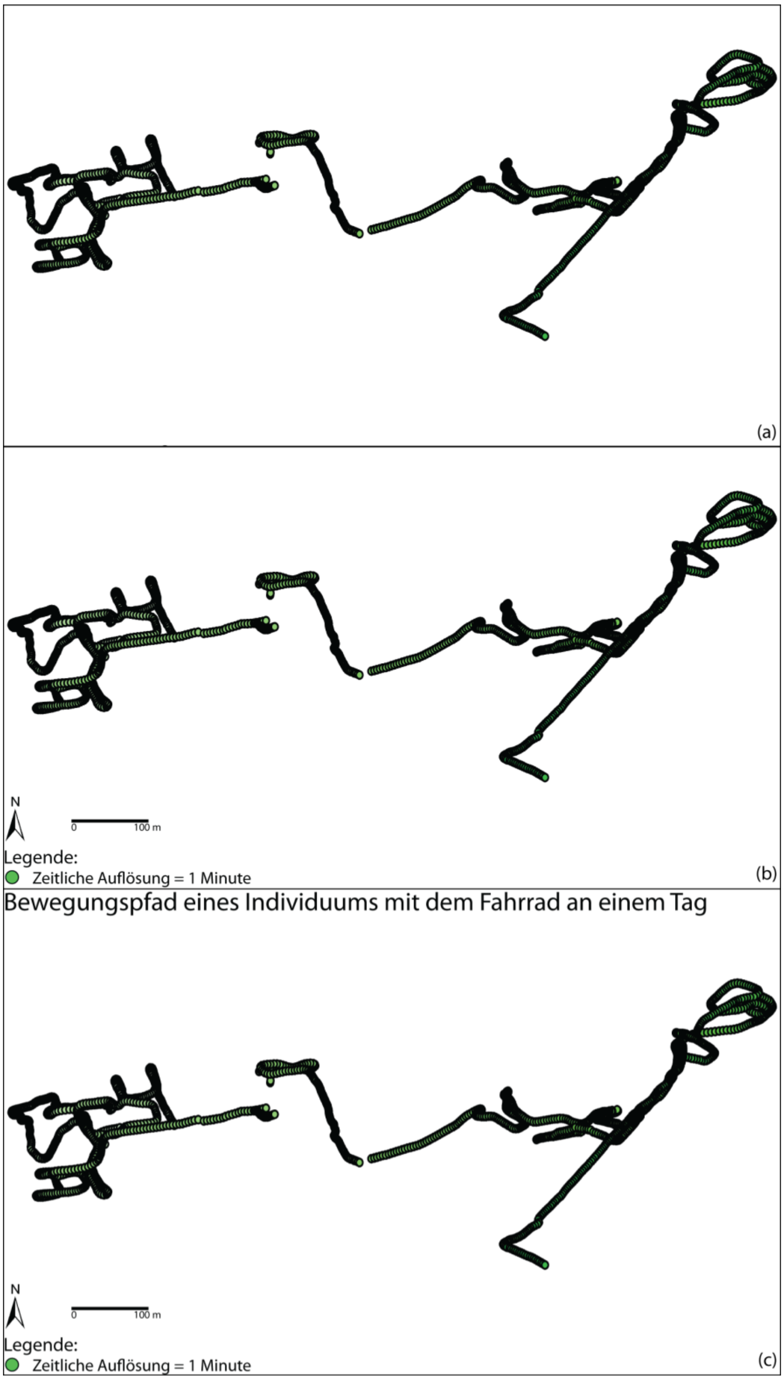


Figure 13: Context conditions for Experiment I

I used bicycle movement data from OpenStreetMap to construct movement trajectories in ESRI's Tracking Analyst. All stimuli were prepared by first converting a *.kml file from OpenStreetMap to a plain *txt file, and then creating a layer in ArcMap. All points from the GPS signal were colored in green and slightly enlarged. I then exported the map to Adobe Photoshop to extract useful parts of the overall trajectory. The stimuli were finalized in Adobe Illustrator by placing red circles (or arrows for velocity) to indicate different answer possibilities. Figure 14 shows (a) the full bicycle trajectory for the first part of the experiment, and (b) a stimuli with answer possibilities for the second part of the experiment.

Six sections of the full trajectory were used to generate more detailed stimuli to allow participants the identification of movement parameters, e.g. speed, duration etc. In order to provide enough stimuli and to avoid artifacts from specific stimuli, I reflected our six stimuli, i.e. the detailed trajectories were horizontally mirrored. In total I used twelve detailed trajectories, six of them being original parts of the trajectory and six reflected trajectories.

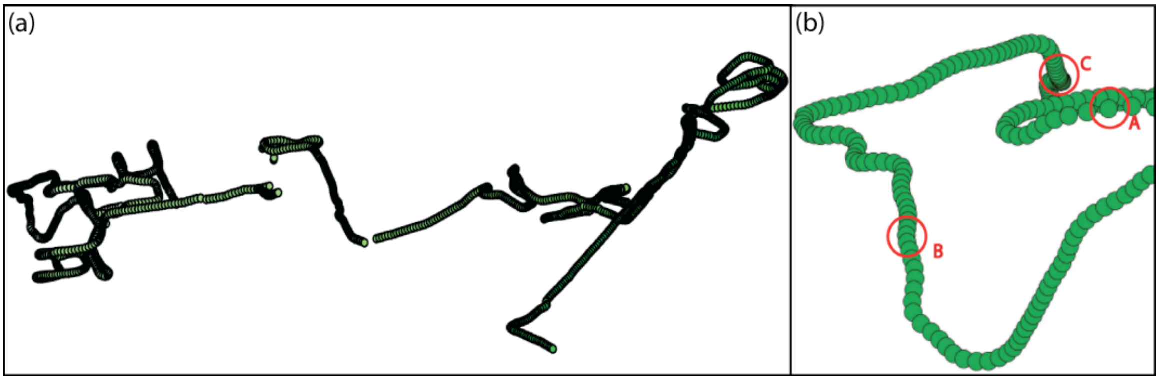


Figure 14: A full trajectory for the overall analysis (a), and a part of the trajectory for the detailed analysis (b)

The overall and detailed movement data analyses were designed according to Shneiderman's information visualization mantra (Shneiderman 1996): "Overview first, zoom, filter, then details-on-demand". The overall analysis is the first part of the experiment and is the identification of any kind of information with the goal to identify a behavioral movement pattern. The first part of the experiment included seven questions and participants were shown the full trajectory. For the detailed analysis users were asked to identify spatio-temporal characteristics, i.e. basic movement parameters as identified in the taxonomy of movement patterns (Dodge *et al.* 2008). This part of the experiment consisted of 15 questions, three questions for each of the five movement parameters, i.e. distance, duration, speed, velocity and position. I constructed three questions per movement parameter to ensure that participants answered coherently. I therefore had three blocks with each five questions. The five questions within each block were randomized. As shown in Figure 14, participants had to chose the correct answer from three possibilities, indicated by red circles at specific locations (A, B, C). Arrows indicated the movement characteristic velocity, as shown on the right side of Figure 14.

Figure 15 shows the design of the experiment. The left column shows the individual parts of the experiment, while the right column shows the number of questions for each part.

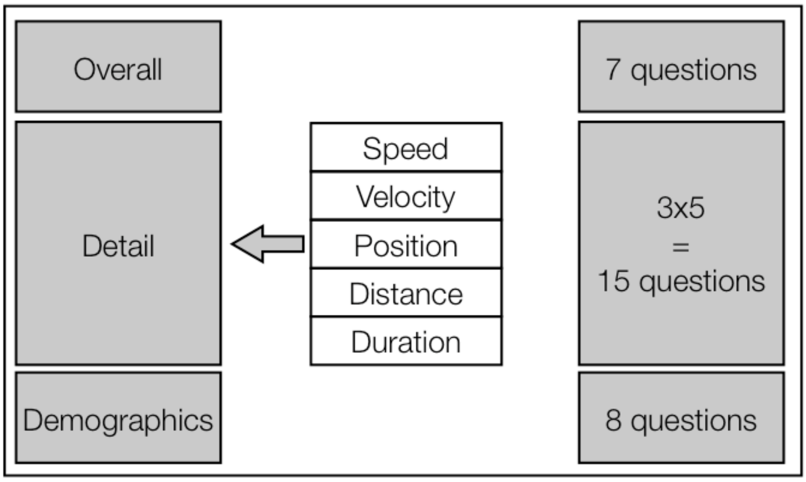


Figure 15: Individual parts of the experiments and the number of questions for each part

A pilot experiment was conducted with three participants in the eye movement lab at the University of Zurich and four additional participants tested the questionnaire online. Minor changes had to be made about the wording of the test questions. The pilot test revealed that some of the stimuli were larger than others. I therefore set the width of the stimuli to an identical size (650 pixel). The height of the stimuli was different depending on the part the trajectory showed. The highest stimulus had a pixel size of 828, while the smaller ones were all at 468 pixels. Due to potential learning effects during the experiment, we disabled the back function of the browser.

The online questionnaire was conducted using a commercial survey software (www.onlineumfragen.com) and was presented to the participants through a standard web browser in our eye movement lab. The eye movement lab is equipped with an active, near-infrared enabled remote video eye tracker (Tobii X120). The eye tracker was configured to record at 60Hz sampling rate. The screen was a 21-inch screen with a screen resolution of 1280*1024 pixels. The eye tracker was calibrated at the beginning of each experiment for each individual participant. All participants were assigned to a condition by their order of appearance, i.e. participant 1 had condition 1, participant 2 had condition 2, and participant 3 had condition 3.

5.1.3 Procedure

Participants had to come to our eye movement lab at the Department of Geography at the University of Zurich to take part in the experiment. The experiment was conducted in German to avoid language problems and to ensure that all participants were able to fully understand the task. Participants first got an explanation how the eye tracker works. All subjects signed a consent form that informed them about the data collection, the usage of the data, the eye tracker and the purpose of the study before the experiment started. Then the eye tracker was calibrated for the participant. The experimenter stayed in the eye movement lab and was available for questions or potential software problems.

Participants were introduced to current movement data and to current collection methods by GPS, mobile phones, etc. Participants were presented with the displays of movement trajectories and were asked to first perform overall and then detailed analyses. The overall analysis showed the full trajectory and consisted of the following seven questions (with answer possibilities). An example stimulus can be seen in Figure 16, which shows an example display for the third question, in which participants had to identify the moving object.:

> Can you identify a pattern in this movement path? (yes, no)
>
> If yes, what kind of pattern can you identify? (open text field)
>
> What object do you think has made this path? (animal, human, eye)
>
> What do you think has the object been doing? (search food, search information, shop, walk, bike, defend)
>
> How long has the movement taken in your opinion? (1min, 1hour, 1day, 1 month, 1 season, 1 year)
>
> How large is the space covered by the movement? (1qm, 100qm, 1ha, 1qkm, 10qkm, 100qkm)
>
> To which extent do you think are the following aspects relevant for your analysis? (irregularities, turns, length, intersections, patterns)

Then followed the 15 questions where participants had to identify movement parameters by choosing one of three answer possibilities indicated through red circles. Figure 17 shows an example display of the detailed analysis.

Figure 16: Example display of the first part of Experiment I (overall analysis)

Figure 17: Example display of the second part of Experiment I (detailed analysis)

At the end of the second part of the experiment, participants were asked to provide background information, such as age, gender, or their experience with GPS data, and experience and usage frequency with movement analysis software. The experiment took approximately 15 minutes.

5.1.4 Results

The next section first presents the results of the statistical analyses. The statistical analysis is run with all 66 participants, including participants who have only participated in the online questionnaire (i.e. without eye tracking). The statistical analysis is therefore calculated with 22 participants for each context condition.

Figure 18 shows the responses for the first question, which asked if participants see a pattern in the representation of the full movement trajectory. In total 16 participants (24%) were able to make out some kind of movement pattern, while 50 participants (75%) did not see any pattern. It is interesting to note that in each condition a majority of the participants did not see any patterns. Also, the more context information was provided, the finding of a pattern decreased (see Figure 18).

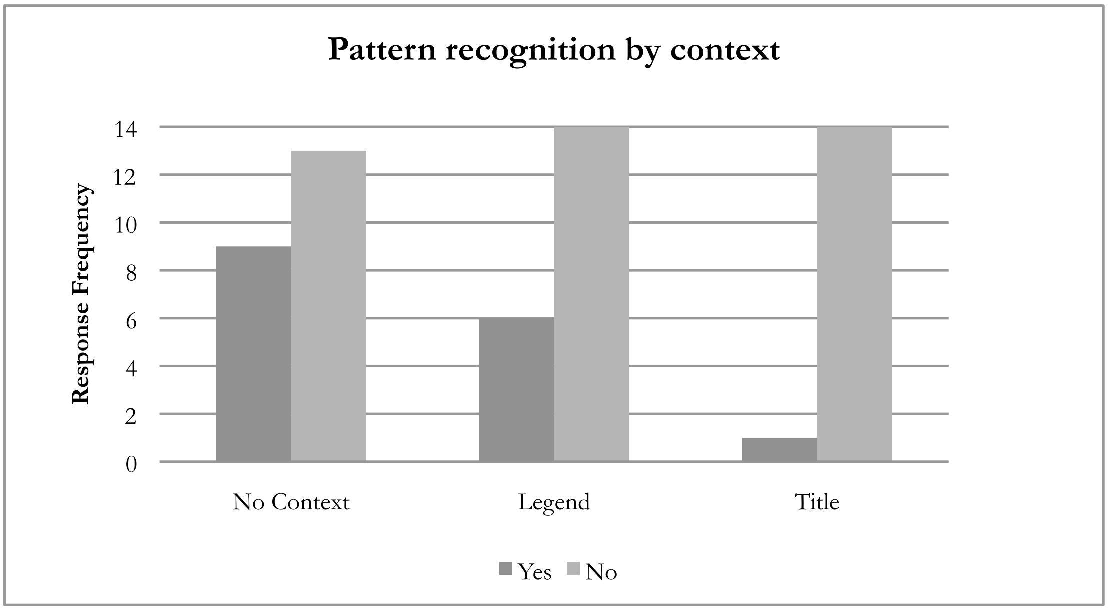


Figure 18: Pattern recognition by context for Experiment I

Sixteen participants (25%) overall have identified the moving object correctly as human. Numbers were higher, as expected, in context condition 3 (including title information), where 12 (18%) participants identified the object correctly. 25 participants (33 %) mentioned "eye movements", as shown in Figure 19. Even when a title was presented which identified the object and its behavior, still 6 participants (9%) chose to respond eye movements. This is surprising and might have happened because eye movement data most likely appeared to be fascinating and novel to most of the participants. Additionally, the participants were seated in front of an eye tracker when responding; often for the first time in their life, and probably considered the likelihood of eye movement data as fairly high.

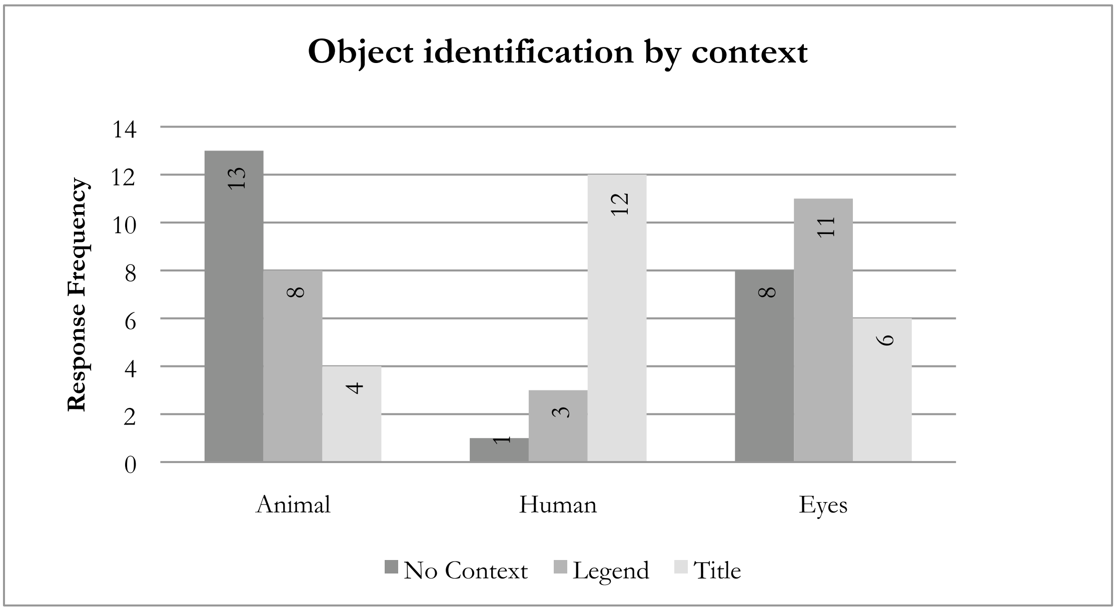


Figure 19: Object identification by context condition for Experiment I

The behavior of the moving object was identified correctly by 0% percent of the participants without context information (see Figure 20). Participants without any context information or legend information most often identified searching for food and searching for information. 50% of participants with title information chose biking as the behavior of the object. This makes sense, as the title information revealed that it was a bike movement. However, it is surprising that the other 50% of the participants chose other behaviors, such as information search, food search, shopping and strolling. Shopping and searching for food could possibly be considered when imagining that you can do these activities also by bike. However, this allows the suspicion that most participants did not see the title, did not consider it, or did not find it relevant for the task at hand. This will be discussed at a later stage again (see Discussion, Chapter 6.1).

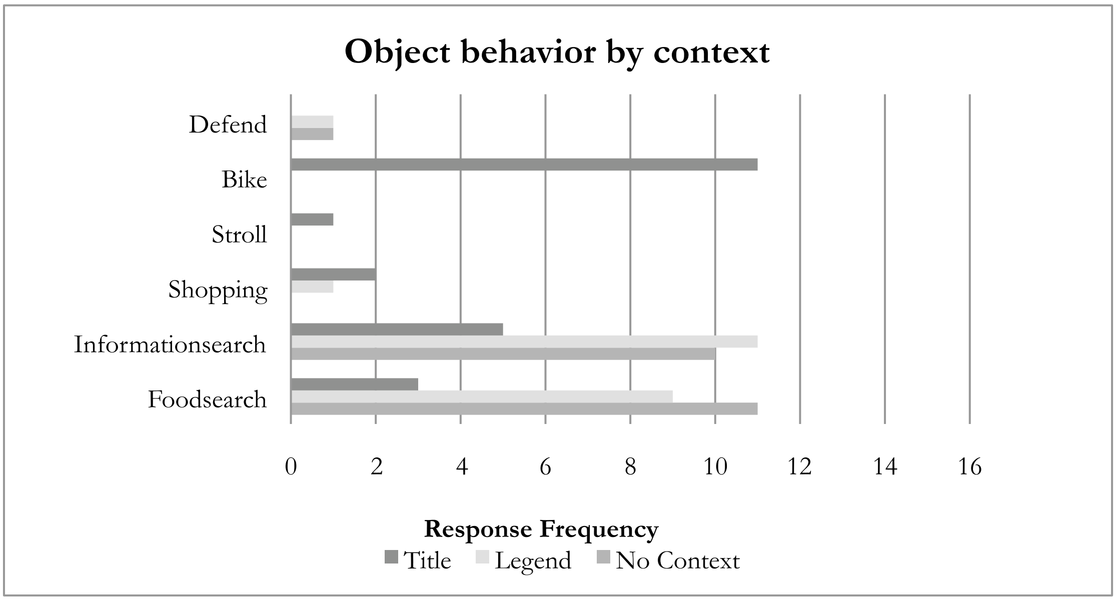


Figure 20: Recognition of object behavior by context for Experiment I

The following section describes response accuracy for the identification of movement parameters. All figures show error bars, which represent the standard error of mean. Figure 21 shows the relative accuracy means for the three context conditions for all questions of the detailed analysis. The mean for "no context information" (M=60.6%) is only slightly lower than for the second condition with legend information (M=60.9%) and full contextual information with a title (M=67.9%).

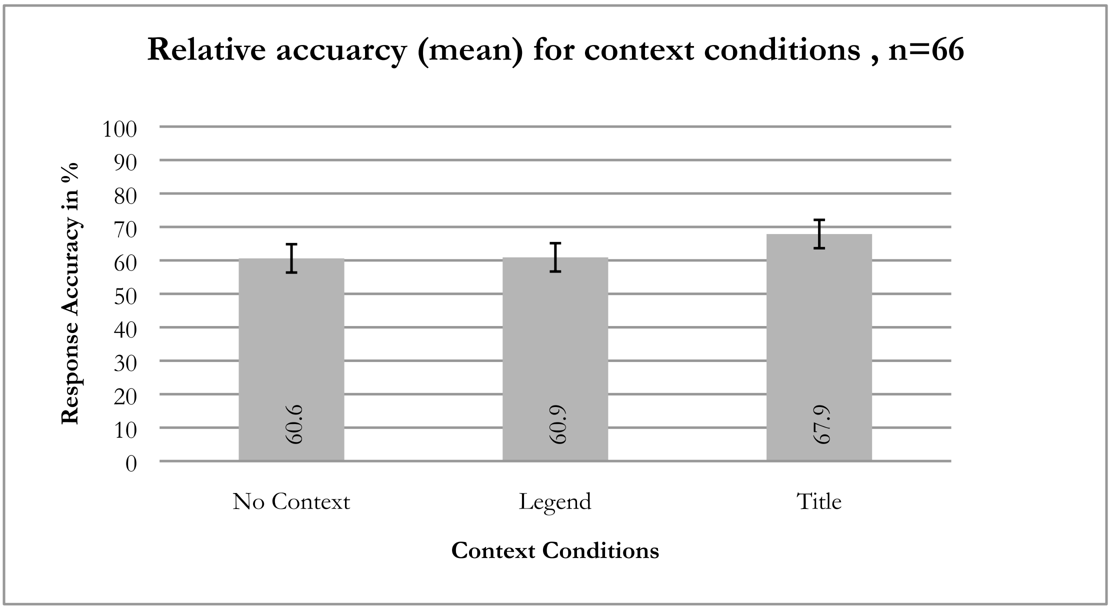


Figure 21: Relative accuracy across context conditions in Experiment I with standard error of means

Accuracy differences can be observed when comparing mean values for the movement parameters (compare with Figure 22). Speed (M=76.26%), velocity (M=71.21%) and position (M=74.24%) are more accurately identified than distance (M=50.0%) and duration (M=43.94%).

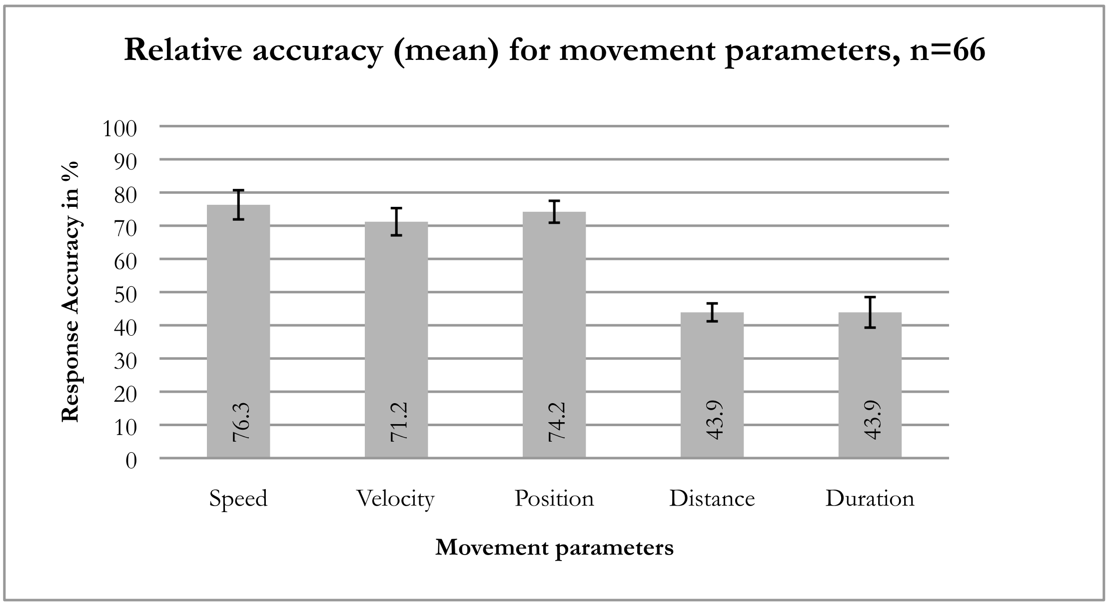


Figure 22: Relative accuracy for five movement variables with standard error of means

Considering the different context conditions shown in Figure 23, we can see hardly any difference for individual movement parameter for the "without any context" and "legend" conditions, while participants performed slightly more accurate with "title" condition. Figure 23 shows that speed is detected more accurately without any context information, while all other movement parameters show an increase in performance with additional context information.

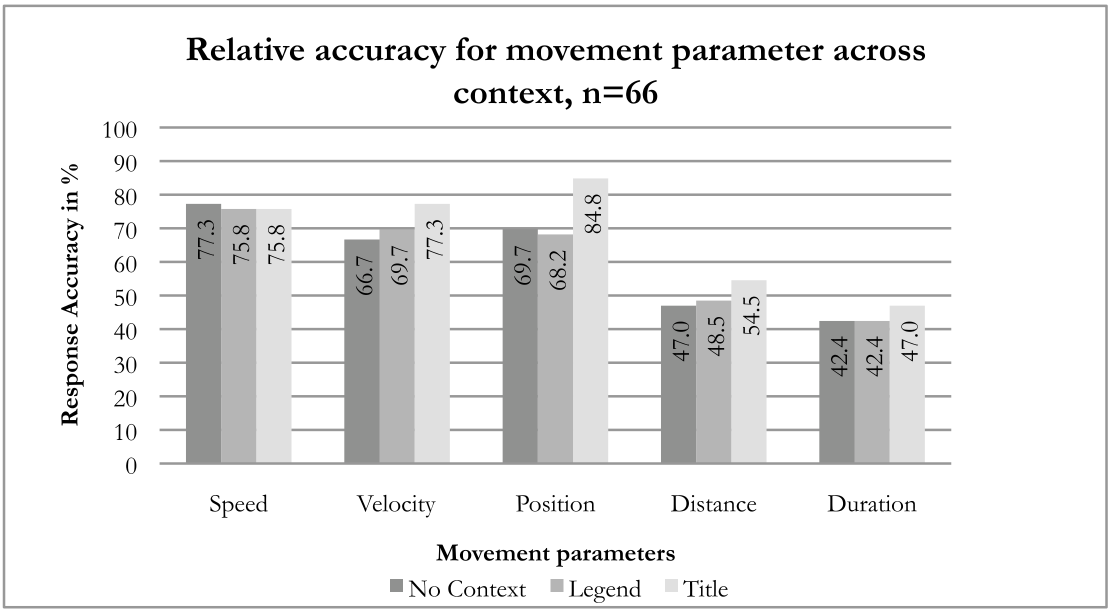


Figure 23: Relative accuracy for movement parameters across context for Experiment I

An analysis of variance has been calculated to assess the effect of contextual information in visual displays. There was no significant effect of context on participants' response accuracy at $p<.05$, for the three context conditions (i.e. without any context, with a legend, with a legend and a title) $F(2,63)=.943$, $p=.395$. This result suggests that context information does not have an influence on participants' response accuracy for the identification of basic movement parameter.

I also investigated participants' **response time (i.e., efficiency)** for the detection of movement parameters. Figure 24 shows that the mean response time across context conditions is almost equal with a difference of about 1 second.

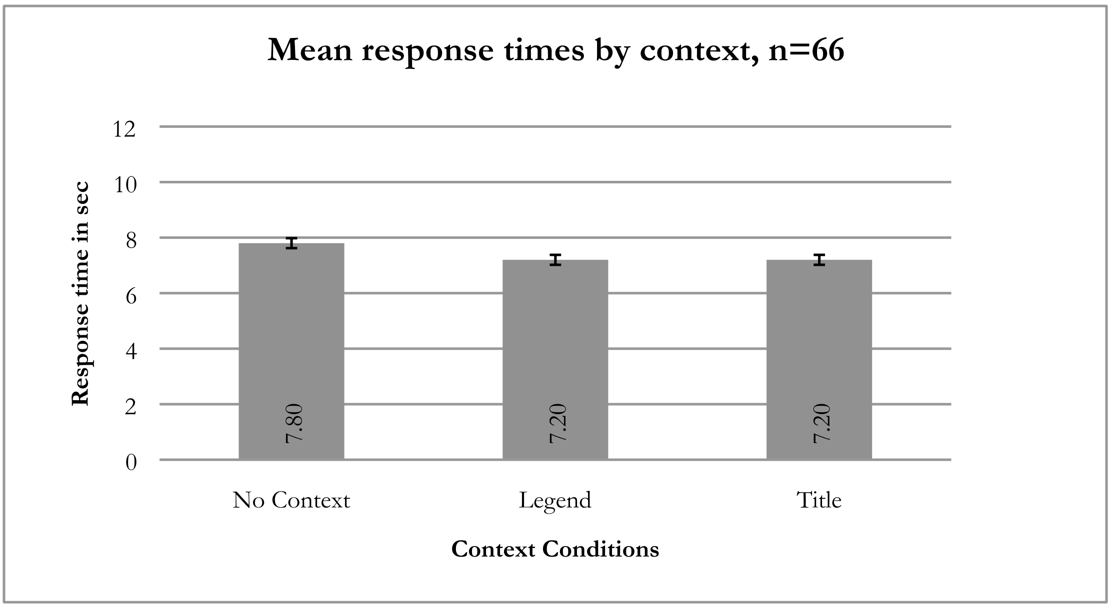


Figure 24: Efficiency of participants by context condition

However, participants were more efficient to identify speed (M=.086), velocity (M=.091) and position (M=.090) in comparison to distance (M=.159) and duration (M=.184), as Figure 25 shows. Participants therefore not only perform more accurately with these movement parameters, but also more efficiently.

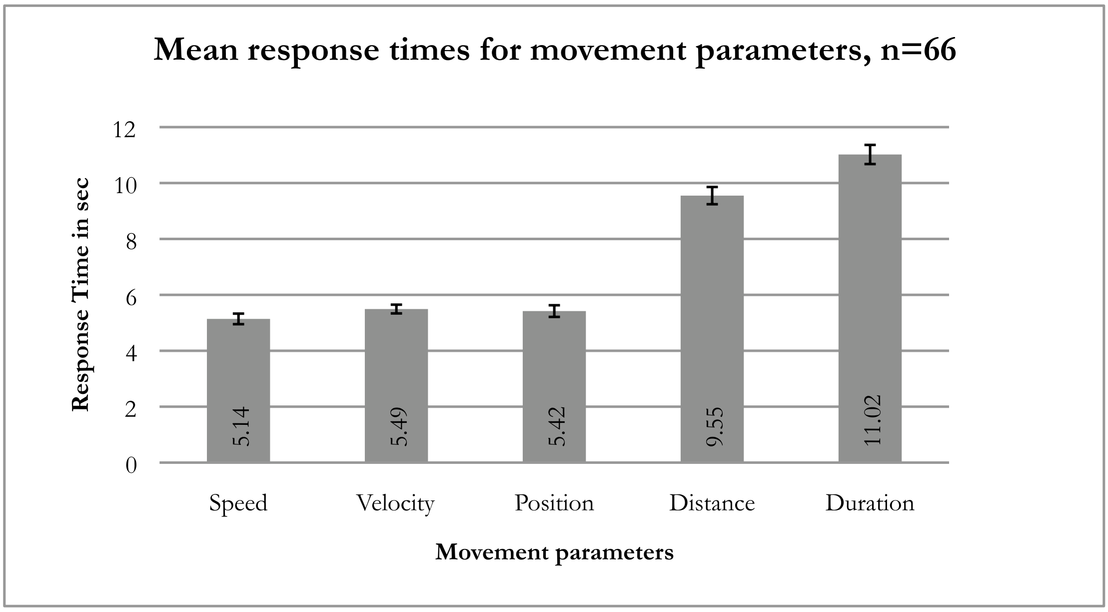


Figure 25: Mean response times for movement parameters

Overall participants take longer to respond to distance and duration compared to speed, velocity, and position. There was no significant effect of context on participants response time (i.e. efficiency) at $p<.05$ for the three context conditions $F(2,63)=.642$ $p=.529$. The result therefore suggests that context does not influence participants' efficiency (compare with Figure 26).

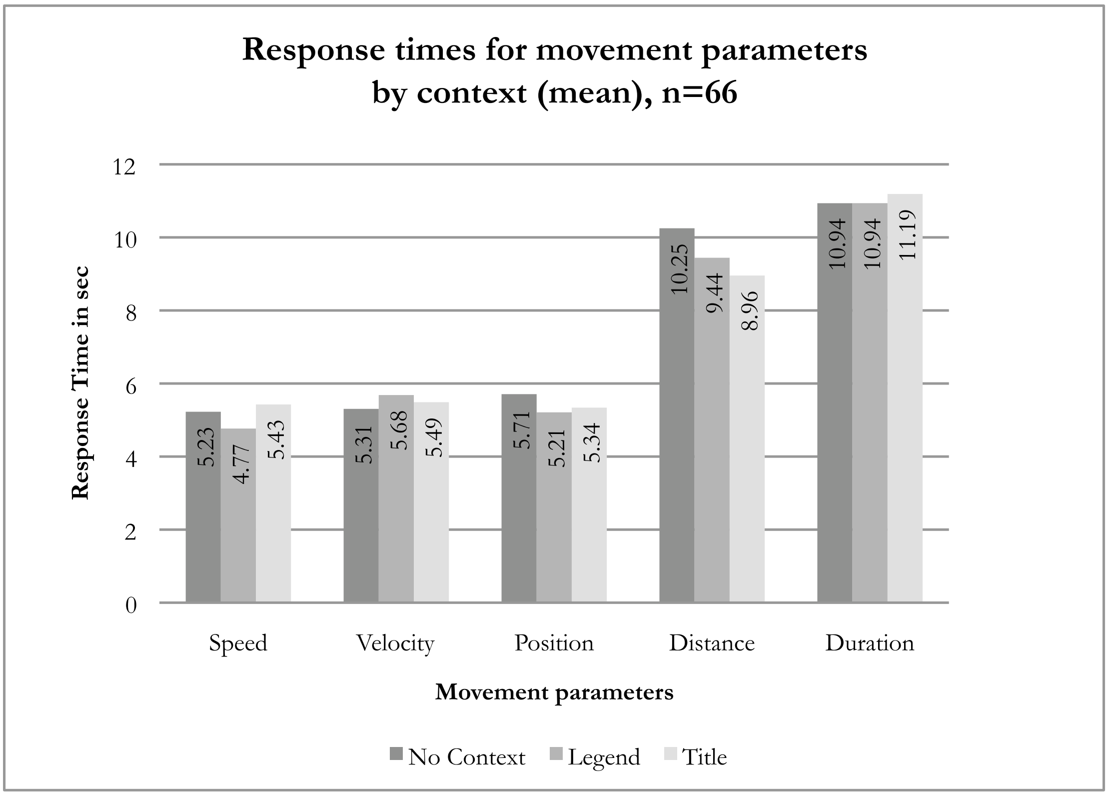


Figure 26: Response times for movement parameters across context

Eye movement analysis was employed as an additional efficiency metric to the response times described before. The time to first fixation in areas of interest (AOI) is a classic metric in eye movement research. It can be employed to identify how long participants take to first fixate a particular AOI and in which sequence the AOIs in the display are first fixated (Goldberg and Kotval 1999). This metric allows us to additionally investigate the efficiency, i.e. detection speed, of particular areas of the stimuli and to differentiate potential search behavior for specific individual movement parameters. For each stimulus, I delineated an area of interest (AOI) in Tobii Studio (i.e. an eye movement recordings analysis software) by creating polygons for legend and title information, as well as for the main area representing the movement trajectory. The AOIs of the stimulus in the first part of the experiment (i.e. overall analysis) were those parts of the trajectory that were more complex, such as 'circular' movements at the right side of the trajectory, the data 'jump' in the center of the stimulus, as well as the more 'complex' part at the left side of the trajectory (as shown in Figure 27). The AOIs in the second part of the experiment (i.e. detailed analysis) were (additionally to legend and title information) the answer possibilities indicated through red circles.

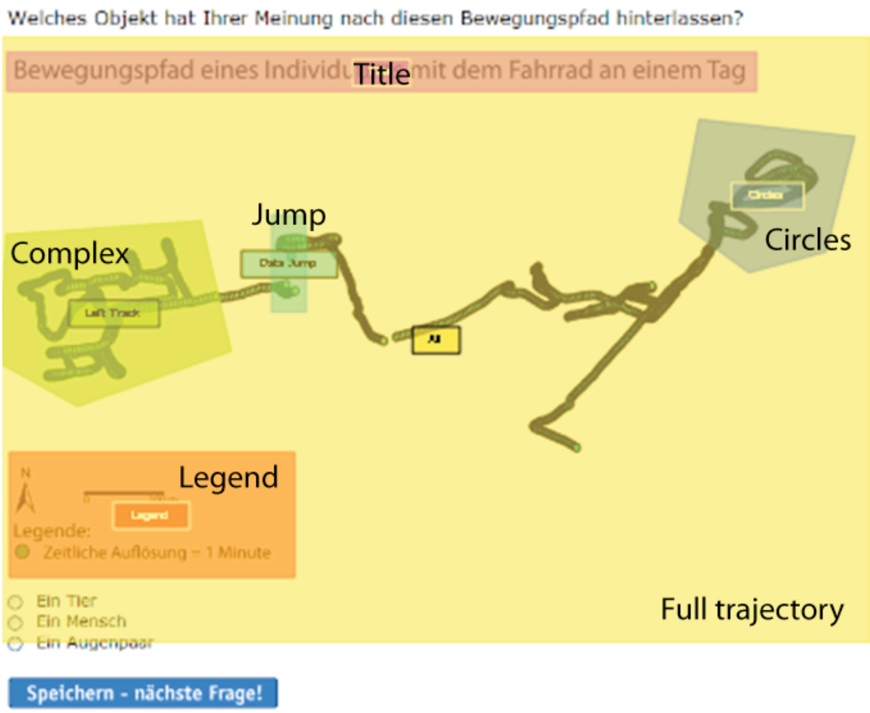


Figure 27: Areas of Interest (AOI) for the overall trajectory with full context information

Before being able to actually analyze the data, I had to prepare the data sufficiently. Tobii Studio allowed me to export all *time to first fixation* metrics for the respective stimuli in text file. Each condition and each stimulus were exported separately, resulting in 66 individual files. The three context conditions were combined in Microsoft Excel and generated 22 files. While preparing the data, two data entries caught my attention: Tobii Studio codes all missing values as -1.00, while 0 is recorded when the participant does not fixate at a certain area of interest in the stimulus. Missing values can appear in eye movement recordings, for instance, when participants in the condition without any context information neither see a legend nor a title. This results in a missing value data entry for the legend and the title AOI. Another reason why missing data can occur is if the eye tracker loses its signal during a recording session. Participants were excluded from the analysis if data was missing for all relevant areas of interest in one stimulus or a series of displays. If only one area of interest (out of minimum of four AOIs) in a stimulus was missing the participant was not excluded from the sample. To be able to run an analysis with missing values, I pre-processed the data by computing the series mean as a value for the missing entries. This was done individually for each context condition. The advantage for this procedure is that "true" missing values for legend and title AOIs in the condition without any information will remain a missing value (as there is no series mean), while all other missing values are assigned the series mean. One should note that it was only a maximum of two values per context condition that were missing per AOI, i.e. a maximum of 2% of the data. Using the series mean is a reasonable measure to calculate the missing values.

The results show that participants looked at contextual information first when presented with the stimuli to identify the moving object (i.e. second question), before analyzing the trajectory. This is true, both when asked to identify which object has made the trajectory as well as when identifying the object's behavior. To identify the object, participants with full contextual information (legend and title) first examined the title (M=1.63 sec), before looking at the legend (M=6.76 sec), and finally the trajectory itself (M=7.02 sec). Similarly, if only legend information was available, participants studied the legend first (M=3.30 sec) before looking at the trajectory (M=3.68 sec). The relatively short time between the legend mean and the trajectory mean suggests that not all participants have looked at the legend. It is also interesting to note that participants studied the trajectory from left to right, thus the common reading-direction in Europe. The "complex" area of interest is on the left side of the trajectory, the "jump" in the data is in the center and the "circles" are at the right side of the trajectory (also compare with Figure 28).

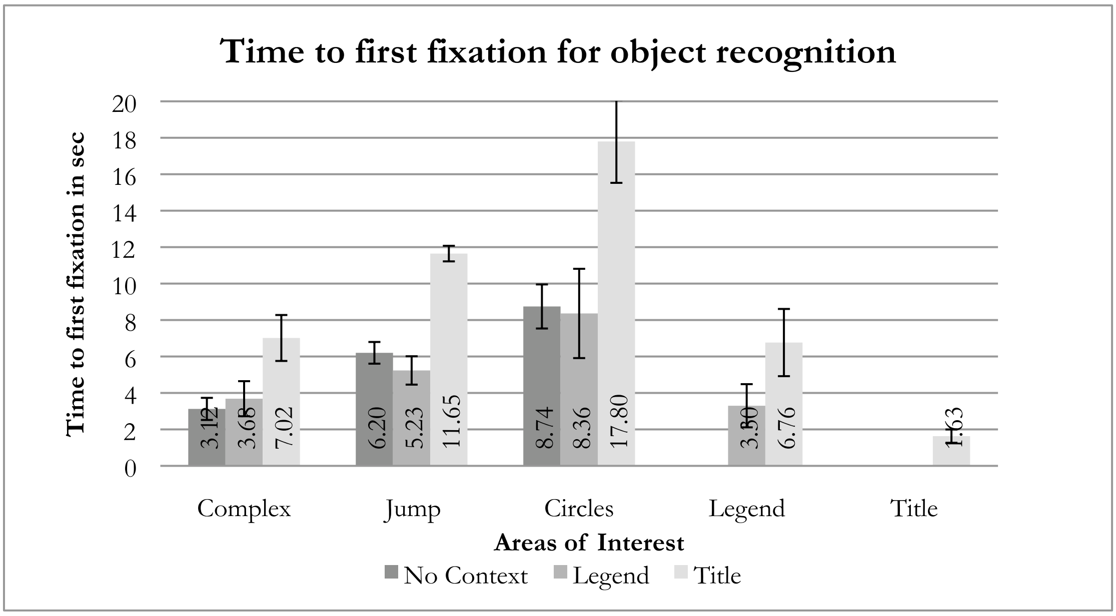


Figure 28: Time to first fixation for object recognition across context

For the recognition of the object's behavior task, I find a similar pattern of fixation sequence as for the object recognition task, as Figure 29 shows. When no context information is presented, participants looked at the trajectory from left (M=5.08 sec) to right (M=10.19 sec). However, if context information is available, participants use this information first before studying the trajectory. In the title condition, participants needed on average 2.85 sec to look at the title, followed by the legend (M=6.59 sec). In the condition with a legend, participants also focused first on the legend information (M=2.36 sec), before looking at the rest of the trajectory.

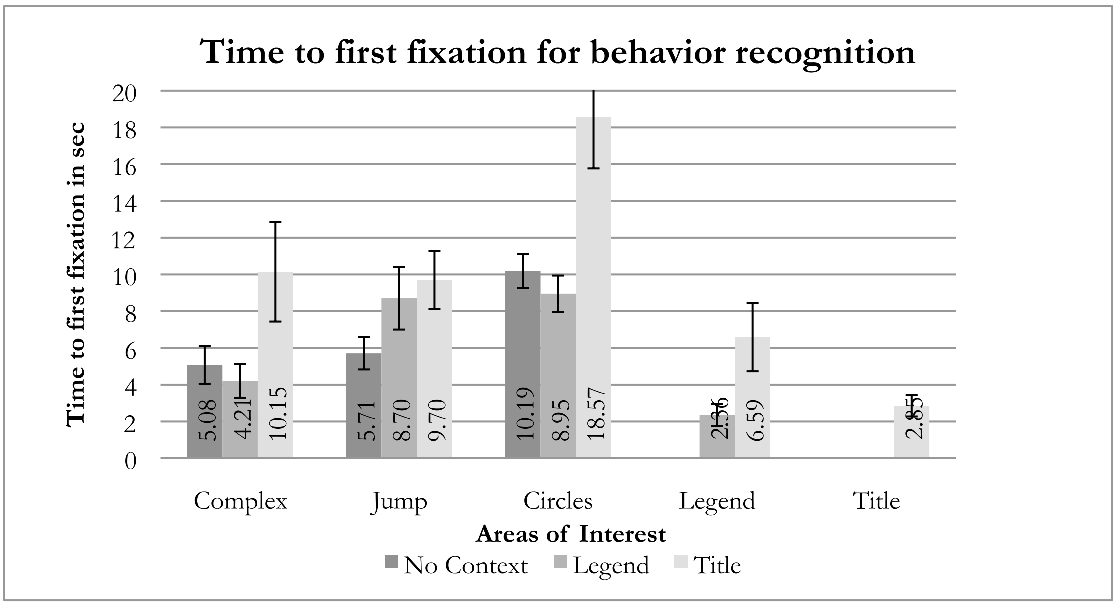


Figure 29: Time to first fixation for Behavior Recognition

In the second part of the experiment (i.e. detailed analysis) participants had to identify five movement parameters, which are reported now individually.

For position information we can see a similar response pattern as for the overall analysis (also see Figure 30). When context information is provided, participants looked at it, before examining the individual answer possibilities. The title was inspected on average after 1.9 seconds, followed by legend information (M=4.93 sec) and then the answer possibilities, i.e. the red circles labeled A, B, C on the trajectory. The answer possibilities for position information were examined in a fairly homogenous manner, i.e. a clear sequence of CBA is detectable.

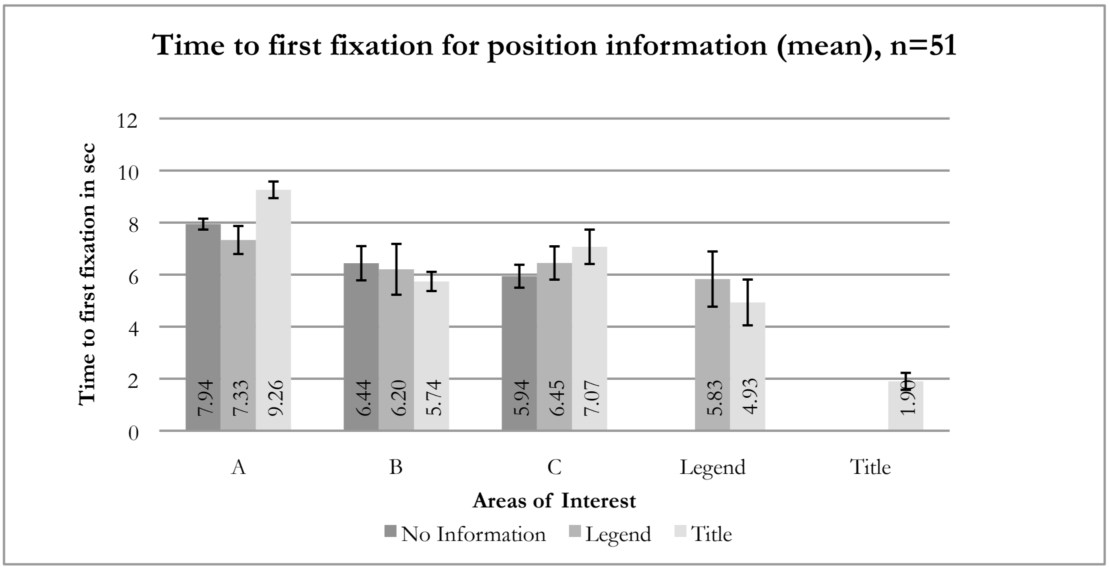


Figure 30: Time to first fixation for position information in seconds

The detection of speed shows a slightly different picture. First of all, there is no clear fixation sequence of where participants looked first when analyzing the mean response times for this stimulus, as Figure 31 shows. Therefore all conditions are examined individually. Participants with no context information first looked at B (M=4.41 sec), followed by C (M=5.87 sec) and finally looked at possibility A (M=7.72 sec). Participants with a legend examined possibilities A (M=4.33 sec) and C (M=4.95 sec) first, before looking at the provided legend information (M=5.73 sec), followed by possibility B (M=5.74sec). In this case, legend information clearly was not as important. We see another interesting result when looking at the mean time to first fixation in the condition with full context information. The title is in general examined only 1.22 seconds after the stimulus is presented, but the following area of interest participants are looking at is the answer option C (M=5.77 sec). Next, legend information is considered (M=7.06 sec), before analyzing the trajectory again (B with M=7.83 and A with M=8.75 sec).

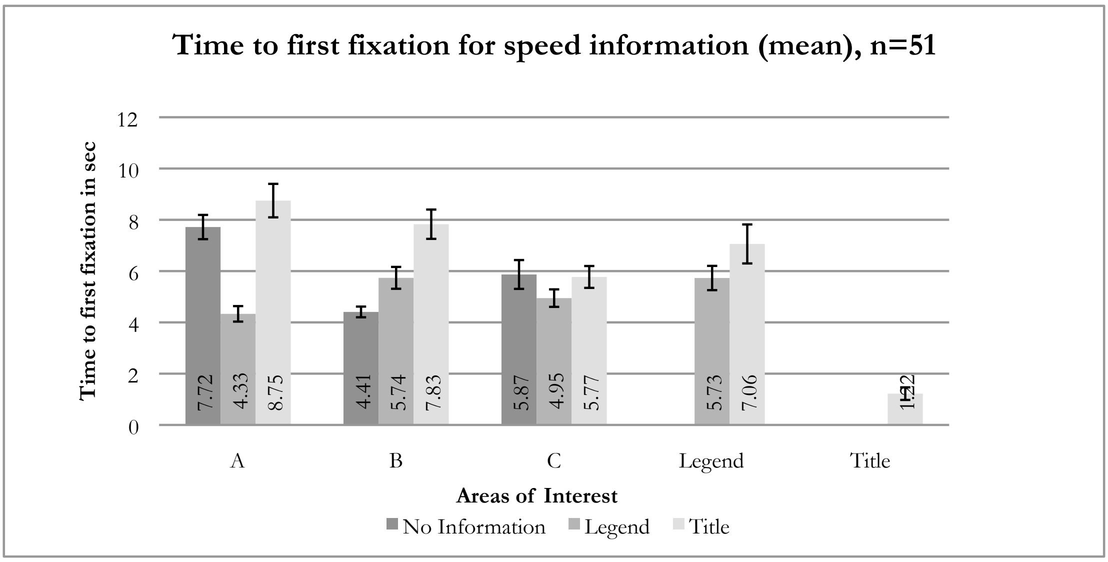


Figure 31: Time to first fixation for speed information in seconds

The sequence pattern for the identification of velocity information is fairly heterogeneous (compare to Figure 32). The time to first fixation sequence for the condition without context information is C (M= 3.43 sec), A (M=3.54 sec), and B (M=4.05 sec). Legend information does not seem to be crucial for the identification of velocity in both conditions with context. The legend is in both conditions examined at the very end, and only after approximately seven seconds (M=7.34 seconds for legend condition, and M=7.51 seconds for title condition). In both conditions participants examine A (M=3.48 seconds in legend condition, and M=5.16 seconds for the title condition) and B (M=2.89 seconds for legend condition, and M=5.65 seconds for title condition), before examining answer possibility C (M=3.49 seconds and M=5.67 seconds). Similarly to the results of the other two movement parameters, participants identify title information first when a title is provided.

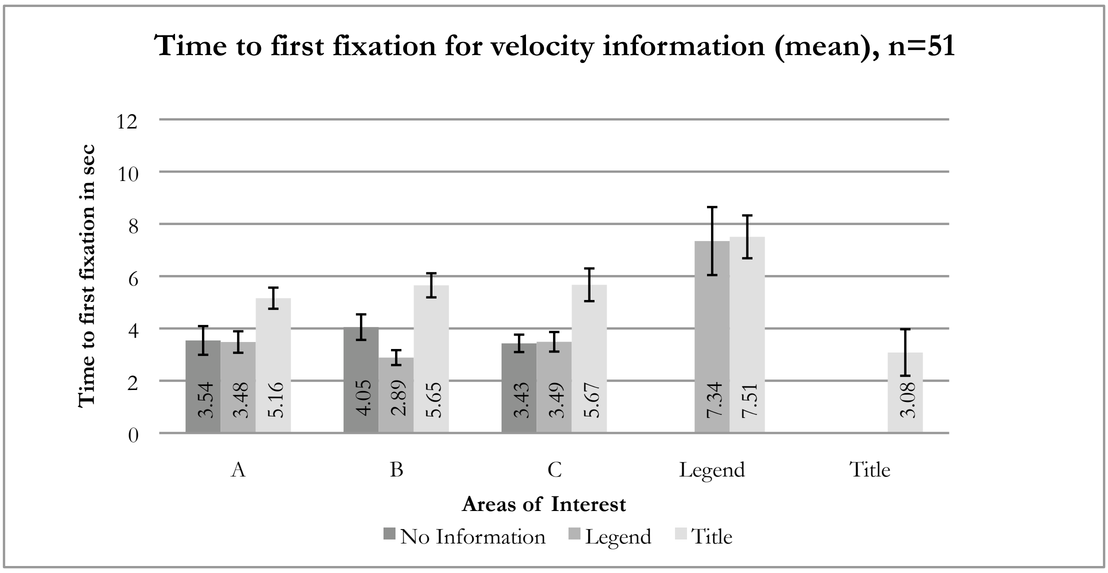


Figure 32: Time to first fixation for velocity information in seconds

To identify the two spatio-temporal movement parameters distance and duration, participants had to compare two pairs of points A to B (AB) and C to D (CD). All participants, regardless of the context condition, first examine the trajectory (compare with Figure 33). The legend information is the last area of interest that is examined. In contrast, title information is examined early on as the second AOI when provided. The CD area of interest is examined first by participants with legend information (M=3.98 sec) and with title information (M=3.79 sec). Participants with no context information first look at AB (M=4.77 sec) before looking at C to D (M=5.06 sec).

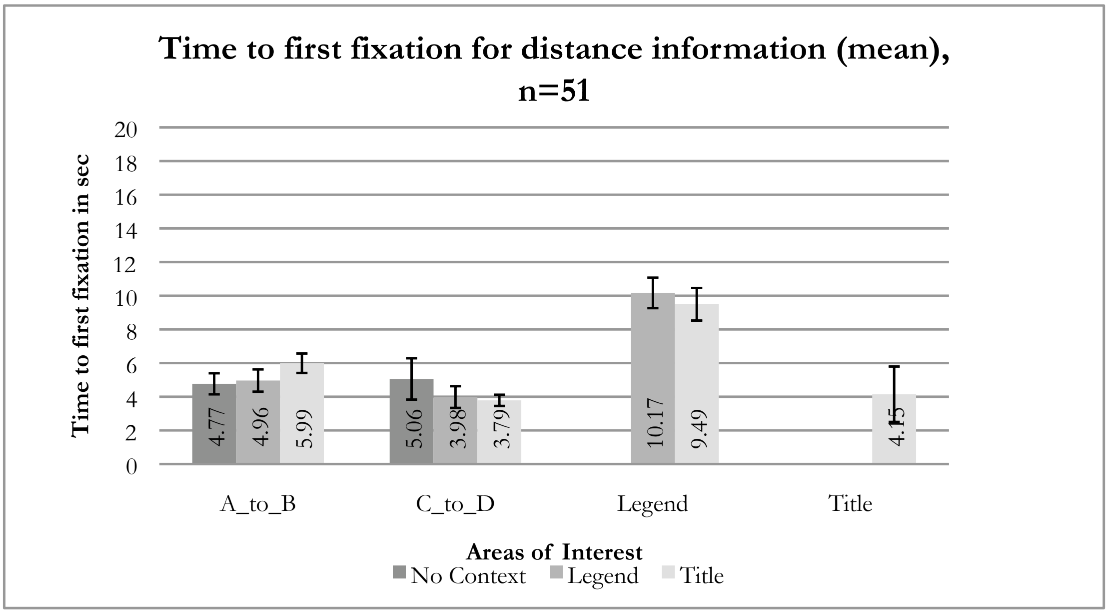


Figure 33: Time to first fixation for distance information in seconds

When looking at the identification of duration information, it is interesting to note that again legend information is the last area of interest to be examined (also see Figure 34).

The answer possibility CD is examined first by participants with no context information (M=3.7 sec) and participants with title information (M=4.76 sec). Participants with legend information first examine the AB area of interest (M=5.78 sec) before analyzing CD (M=6.7 sec) and then looking at the legend. Participants with title information first examine CD (M=4.76 sec), before looking at the title (M=5.67 sec).

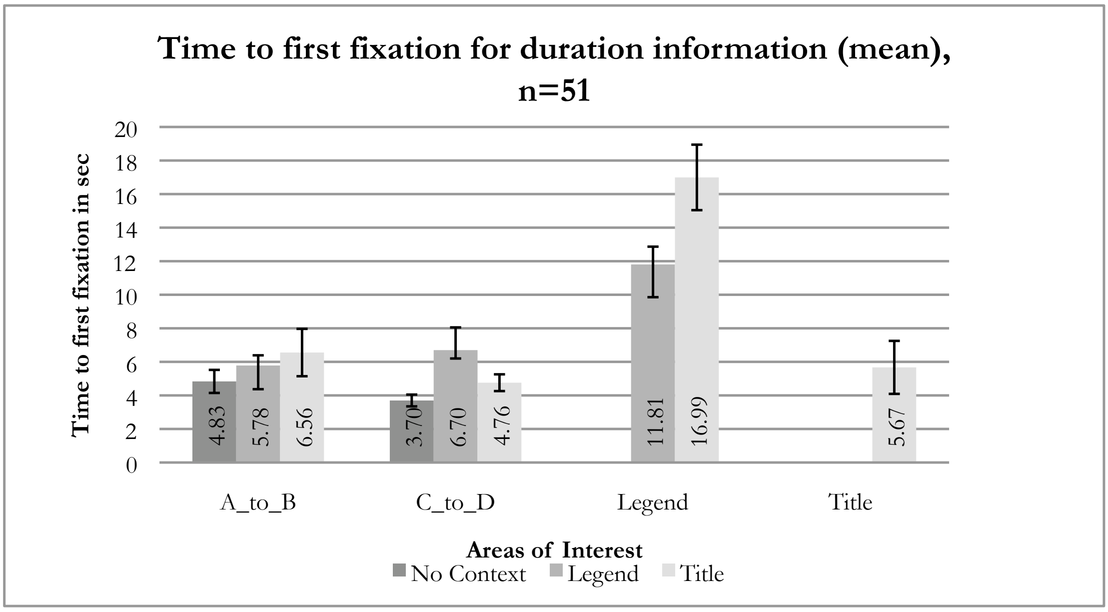


Figure 34: Time to first fixation for duration information in seconds

5.1.5 Summary of Results for Experiment I

The results of the experiment suggest that the identification of the moving object is poor in all context conditions. Hardly any differences are identifiable between the condition without any context information and the legend condition. Most participants chose animals or eye movements as the moving object. In the title condition, more participants chose a human as the moving object as compared to the other conditions, but still almost 50% of the participants were incorrect by stating it related to eye movements. This result is surprising, as the answer was in the title, i.e. bike movement from one day. Similar results are obtained when participants had to identify the behavior of the object. Again, most participants, regardless of the context condition chose 'search for information' or 'search for food' as the behavior. This suggests that the object was seen as either being an animal or eye movements. Even when title information is available still almost half of the participants chose 'searching for information', as opposed to the obvious biking activity. One possible reason for this result might be that participants are biased because they are sitting in front of an eye tracker in an eye movement lab. Probably most participants have never seen an eye tracker or used one, and also do not know how the scan path of eye movements looks like. We think that the novelty of the eye tracker has lead to the assumption that this track could have been made by an eye tracker without taking the title into consideration. Another reason might be that the title information is too obvious, and lead participants to believe that this is a trick question, as some of the participants indicated.

When considering the identification of the tested five movement parameters, we can conclude that context information does not improve the performance of the participants. Nevertheless, participants perform better for the spatial and temporal variables (e.g., position, velocity and speed), as opposed to the spatio-temporal variables (e.g., distance and duration), and an ANOVA confirms a significant difference. Participants' performance is not influenced by context, but rather by the movement parameter that has to be identified, e.g. speed, distance, etc. However, accuracy is still relatively low at 63%. Efficiency is also higher for speed, velocity and position variables, in contrast to distance and duration. In other words, distance and duration are harder to identify accurately and consequently it also takes participants longer.

Results from the eye movement analysis reveal that context information communicated with legend and title is not consistently used throughout the experiment. There might be two reasons for this: Context information does not change during the experiment, i.e. by the time participants start to identify basic movement parameters, the context information has been displayed seven times. Perhaps context information is simply not considered due to a boredom effect. Another reason might be that participants did not need context information to identify movement parameters. All task relevant information is directly observable in the trajectory representation itself as the GPS points are sampled at equal time intervals. Speed information, for instance, can easily be obtained by examining the distance between points, i.e. the closer the points, the slower the object. In this case, context information is not necessary for the identification of basic movement parameters.

To summarize the results of this experiment we find that participants did use title and legend information when trying to identify the moving object and its behavior, and participants' performance increased slightly. A trend can be identified that context information helps to more effectively identify a moving object and its behavior. I can therefore positively answer our first research question:

> **Q1a:** Does extended contextual information, in the form of legend and title, help participants to identify a moving object and its behavior?

However, the results demonstrate that context information does not influence the accuracy of identifying movement parameter. I therefore have to answer our second research question negatively:

> **Q1b:** Does context information help for the identification of basic movement variables, such as distance, duration, speed, velocity, and position?

5.2 Experiment II – geographic context

From the first experiment we have seen that only the accurate identification of moving object and its behavior were influenced by context information by using additional relevant information. The second experiment looks at the environmental setting of the movement, i.e. geographic context. I therefore test if the assumption also holds for geographic context information. This experiment therefore focuses on two questions:

> **Q2a:** Are participants more accurate and confident in identifying a moving object and its behavior having geographic context information?

> **Q2b:** Does it matter for the identification of a moving object and its behavior if a movement trajectory is situated in its true geographic context?

5.2.1 Participants

In total 46 participants completed the online experiment. Out of the 46 participants that completed the questionnaire, two participants were eliminated from the analysis. One participant did the online questionnaire on a smart phone, i.e. with a screen size of approximately 9 inches, which is considered too small to visually examine the trajectory in detail. The second participant suffers from a red-green color deficiency. Since the trajectory in the second half of the experiment is displayed as a red trajectory on a greenish terrain map, I concluded that the visibility of the trajectory is possibly too weak to accurately see the trajectory. Subsequently, 44 participants were analyzed in this experiment. 57% of the subjects were male participants and 43% are female participants. The age of the participants ranged from 20 to older than 60. 68% of the participants are between 20-30, an effect from sending the invitation to students and colleagues. 16% are between 31-40 years old, 14% are between 41-60 years, and only 2 % of the participants are older than 60 years.

5.2.2 Experimental Design

The independent variable is geographic context information, and has two treatment levels. The first treatment level is without any context information, i.e. the trajectory is displayed on a homogenous background. The second treatment level shows a terrain map that locates the movement trajectory into its geographic context, i.e. in the environment.

Human movement data collected for the Mafreina research project (www.mafreina.ch) from the University of Applied Sciences in Wädenswil, Switzerland, was used to construct movement trajectories. The data consists of GPS tracks that were recorded during various outdoor activities in the Swiss National Park. The participants study a single movement trajectory represented by a temporal sequence of GPS fixes, i.e. dots, on a 17-inch sized display. The stimuli are generated by overlaying the GPS tracks on Google Maps. Therefore the GPS-files were mapped employing Google Maps API. The experiment is set up as a two (geographic context) by two (behavioral context) by two (path type) factorial design. The experiment is a within-subject design, with geographic context being the within-subject factor, i.e. participants are presented the trajectory first without and then with context information through a terrain map. To display the trajectory without context information we calculated a small transformation of the longitude coordinates by subtracting 20°. This transformation had the effect that the trajectory was displayed in the Atlantic Ocean and thus the terrain map is simply light blue. When displayed with a terrain map, the map represented the actual location in the Swiss National Park. To strengthen the geographic context information, the terrain map includes cartographic symbols indicating camping facilities. One should note though, that the camp symbols were carefully located at spots where neither the speed, nor the direction of the trajectory changed to avoid any biases caused by movement changes in the trajectory (see Figure 35 for geographic context).

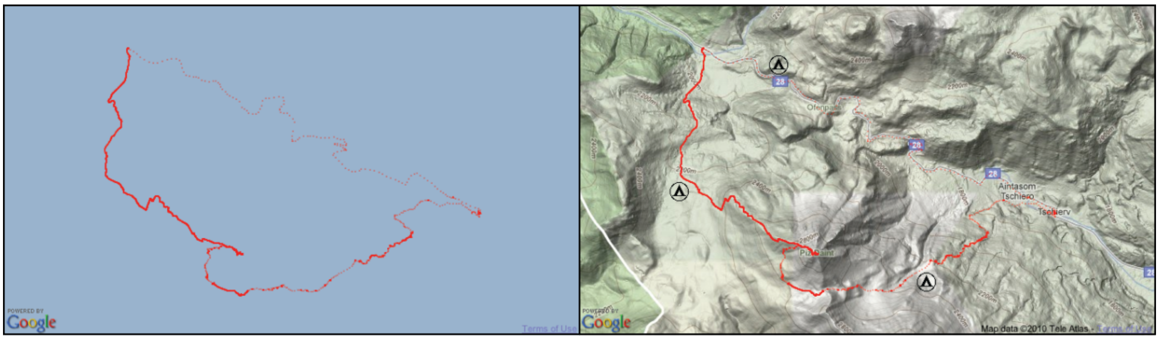


Figure 35: Geographic context is manipulated by (a) a homogeneous background (left) or (b) a terrain map (right)

Behavioral context has two treatment levels and shows eight stimuli generated from movement trajectories from ski touring, while the other eight stimuli show movement trajectories from skiing on slopes (piste). These two (goal directed) outdoor activities create distinctly different movement patterns, as shown in Figure 36. Downhill skiers move (rapidly) downhill within a well-defined elongated area of groomed slopes, always in the vicinity of existing ski lift infrastructure (slower and mostly straight uphill movement). Backcountry skiers on the other hand hike (slowly) uphill in (sometimes meandering) tracks and (more rapidly) ski downhill, unrestricted by human made infrastructure.

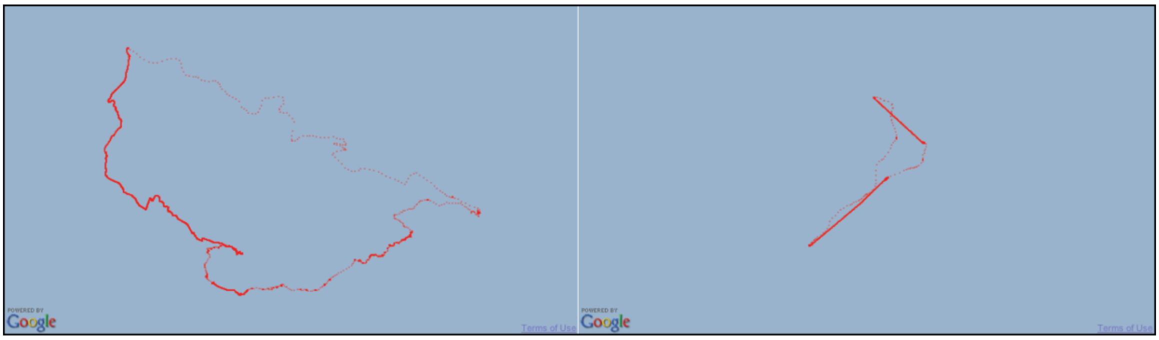


Figure 36: Behavioral context is differentiated by two activities, ski touring (left), and skiing on slopes (right)

In each of these conditions, we have four trajectories that are open and four trajectories that are closed to manipulate the factor path type. Open trajectories have a different starting and end point (marked with O as for example in OTour), while closed trajectories have the same start and end point (see Figure 37 for comparison). The trajectory shape (open/closed) has been hypothesized by prior psychological work to be cognitively and perceptually different (Shipley and Maguire 2008). One half of the trajectories are original GPS tracks, while the others are horizontally rotated trajectories. The reflected trajectories are therefore, when presented with geographic context information, not in their true geographic location.

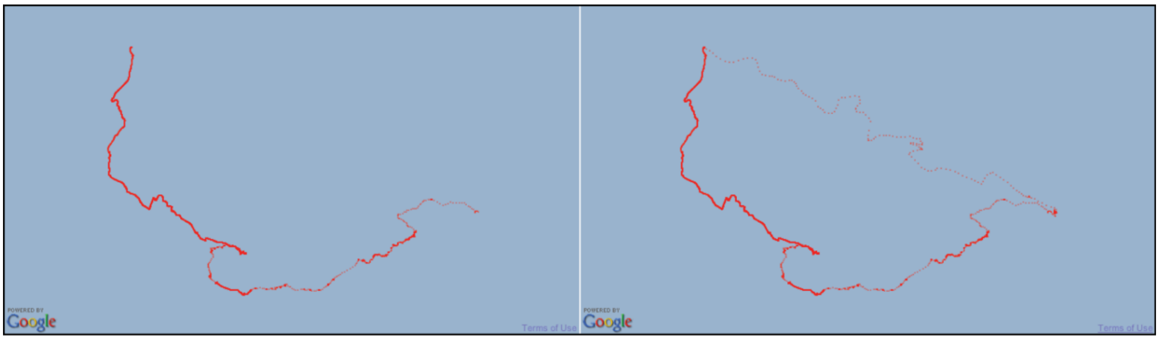


Figure 37: The path type is either open (left) or closed (right)

Table 1 lists all stimuli grouped according to behavioral context (tour/piste) and path type (closed/open). All horizontally reflected stimuli and are marked with _h at the end.

Table 1: All stimuli for Experiment II & III by activity and path type

	Ski touring (Tour)	**Skiing on slopes (Piste)**
Closed	Tour1	Piste1
	Tour2	Piste2
	Tour1_h	Piste1_h
	Tour2_h	Piste2_h
Open	OTour1	OPiste1
	OTour2	OPiste2
	OTour1_h	OPiste1_h
	OTour2_h	OPiste2_h

Each participant answered two qualitative (i.e. open text) questions and two quantitative questions. The dependent variables are confidence and accuracy (from second and third question). The four experiment questions were:

1. What do you think is presented here in red? You can name anything that you consider to be correct.
2. How confident do you feel about your answer?
3. Who or what do you think has moved?
4. What else comes to your mind?

The open questions ("what do you think does the red path show?" and "do you have any additional comments") were intended to get insight into the user's initial idea what kind of object has made the trajectory and maybe getting a hint what information participants used to identify the moving object.

Each participant is shown only four stimuli in each context condition from the 16 stimuli, resulting in four groups of participants. Each group of participants has one open and one closed ski tour trajectory and one open and one closed skiing trajectory. The questions and the stimuli are presented through a web questionnaire designed with www.onlineumfragen.com (also compare with Chapter 4.1.1). The assignment of the participants to the groups was randomized using a *.php script (for details of the script see Appendix). In total, each group had to answer 16 questions for four stimuli without context information and 16 questions for four stimuli with geographic context information. Participants were first presented with the displays without any context information to avoid potential learning effects from seeing the trajectory on a terrain map.

The experiment was piloted in two phases with a total of five students at the Geography Department of the University of Zurich. The first pilot round with two participants suggested that a within subject design is favorable to a between subject design because it allows to see more directly the changes in participants' behavior. In the second round of pilot experiments, participants also tested the presentation of the online questionnaire, and the forwarding from a homepage (with the randomization function). The wordings of the questions were changed to make questions easier to understand.

5.2.3 Procedure

The questionnaire was sent as an online invitation to participate in this experiment. The invitation was sent to approximately 100 undergraduate students of the Department of Geography, as well as to about 100 friends and colleagues. It was not required that participants have a geography background. After getting a first introduction on a website, participants were randomly forwarded to one of the four questionnaires on www.onlineumfragen.com.

Each participant was first presented with four stimuli without any context information. Participants answered the first question by writing their impression into an open text field. In the second question participants rated their confidence on a Likert Scale from one, indicating "very unsure", to five, indicating "very confident". The third question asked if participants could identify the moving object, and participants could choose from one of four options, namely animal, human, nature phenomenon, or machine. In the fourth question, participants could state their additional comments and impressions in an open text field. After four stimuli without context information, participants saw the same stimuli with context information and answered the respective questions.

At the end of the questions, the participants had to answer some personal questions, such as age, gender, their familiarity with GPS data, the screen size they have used, their hobbies, and if they have any red-green/color deficiencies. The experiment took approximately 20 minutes and was conducted completely anonymously.

5.2.4 Data Preparation

Figure 38 shows the workflow for the analysis of this experiment. After the data collection the results can be split into quantitative and qualitative data. The experiment is analyzed in two steps: First, the quantitative data is analyzed and consists of questions regarding participants' confidence and the object they recognize. The second step is the analysis of the qualitative data.

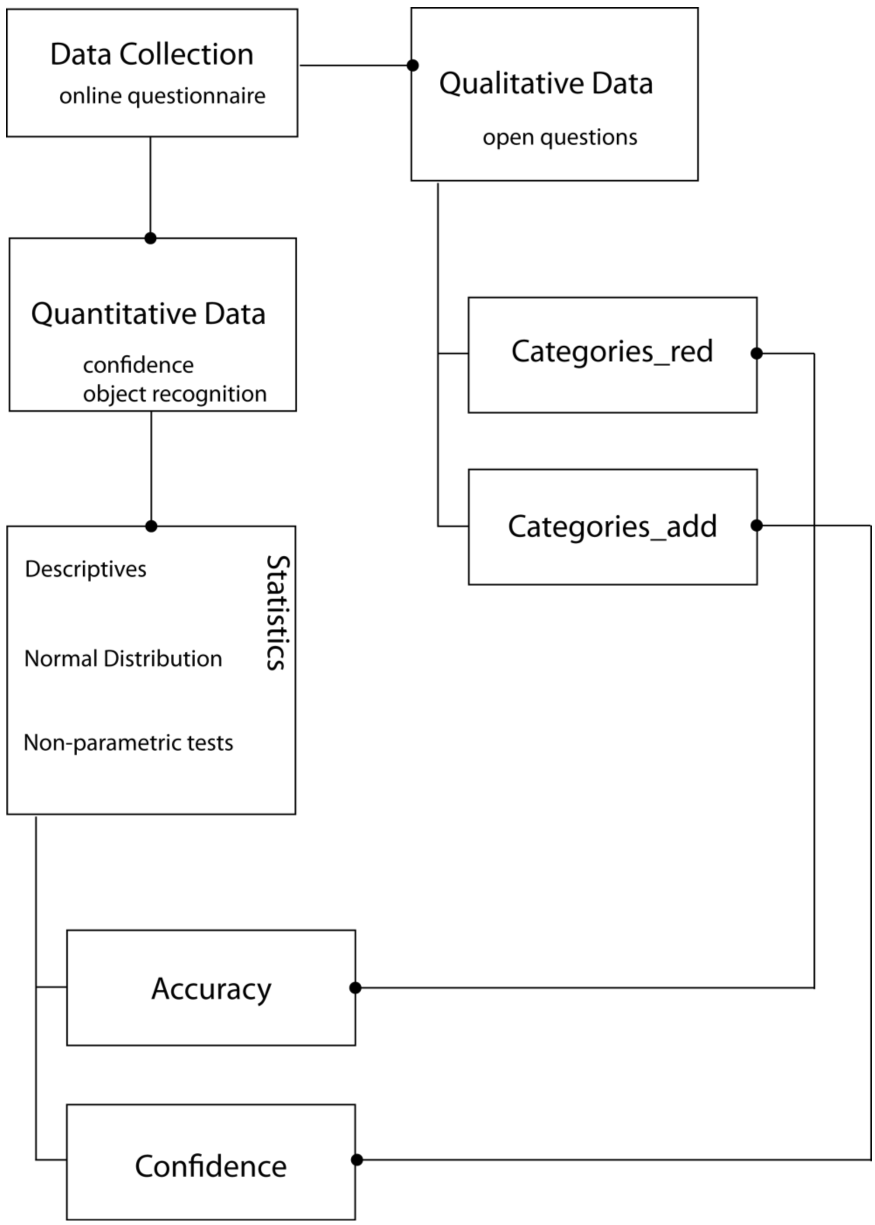


Figure 38: Workflow for the analysis of Experiment II

Before being able to analyze the data of the second experiment, the data had to be aggregated and prepared for analysis. The four individual group files were aggregated into one large file. In a next step new variables were computed that summarized certain stimuli into one, using the respective values from each participant, e.g. the confidence ratings for all ski touring data Tour=SUM(Tour1, Tour2, Tour1h, Tour2h). In this case, the variable is summarized according to the activity, but does not take into account if the trajectory is correct or incorrect in its geographic context. Another aggregation takes into account if the trajectories are open or closed (e.g. OTour). In a second set, I aggregated the data also according to its correctness in their geographic context, e.g. the confidence for all correct ski touring data posTour=SUM(Tour1, Tour2, OTour1, OTour2). In this case, open and closed trajectories are summarized, but we can distinguish between correct and incorrect trajectories. The summary of the results will always look at the aggregated data by path type and then the aggregated data by its geographic correctness. To be able to analyze the accuracy of participants' responses, the data was re-coded into correct and false answers (1, 0). After the data preparation I ran statistics for the quantitative data, following three steps: 1. descriptive statistics, 2. test for normality, and 3. (in this case) non-parametric tests to check significance of accuracy and confidence values.

For the analysis of the qualitative data, categories were established and analyzed. In a first step, I inspected the data to identify possible response categories. Obviously categories are different for the different activities, as the visualizations of the trajectories generate two distinctively different pictures. However, some categories are applicable to both activities, like trajectory of a human, or trajectory of an animal. The identified categories for the first question are:

> Trajectory animal, trajectory human, trail, border, river, region, ski area, data, natural phenomenon, cable car, combination of technical and trail, technical installation, air traffic, other, and no idea.

The identified categories for the second question are:

> Speed, direction, shape, line, open and closeness of trajectory, start and end, clear interpretation ideas, unclear interpretation, and topography.

All answers from participants were evaluated according to these categories. As a result I have response frequencies per category that can be further analyzed. The results of the two open questions reported in the next section are based on these categories.

5.2.5 Results

Confidence

I first report the results of participants' mean confidence ratings. On average participants' confidence rating was 2.87 on a scale form 1 to 5, with a mean confidence of 2.33 without any context information, and a mean confidence of 3.38 when context information was available. In other words, participants feel more confident to analyze a movement trajectory when geographic context information is available, thus allowing the participant to see where the movement has happened.

Examining the results in more detail shows that confidence increases with geographic context information to analyze a movement trajectory, for both path types and activities shown in the display. However, no significant difference is observable when comparing the different path types, as Figure 39 shows.

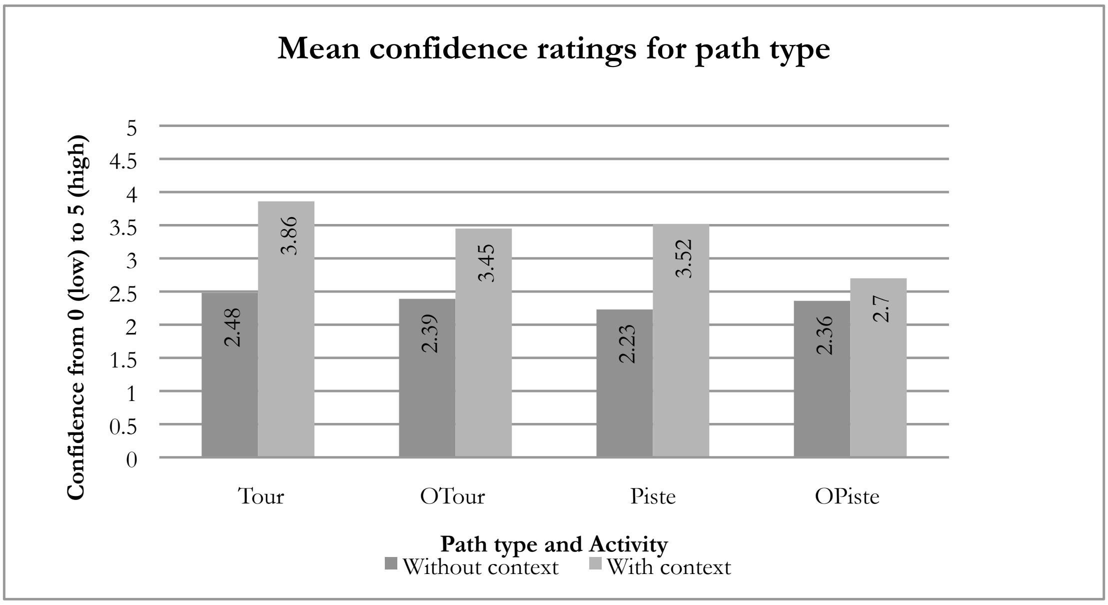


Figure 39: Mean confidence ratings for activity and path type

Similarly, I explored the data according to the correctness of the geographic context, i.e. if the trajectory is situated in its true geographic location.

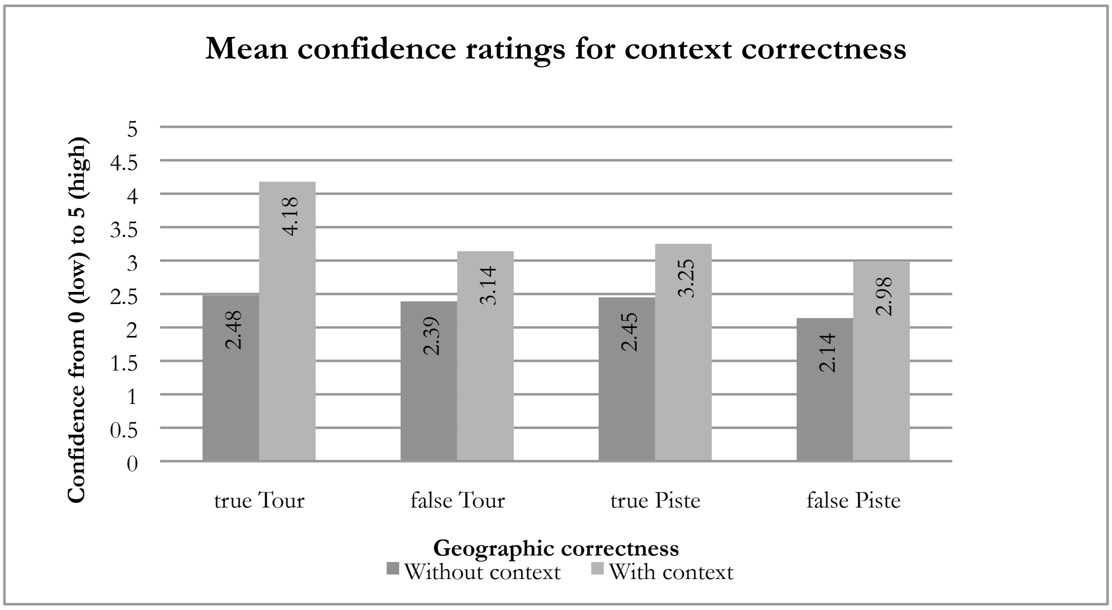


Figure 40: Mean confidence ratings for context correctness

When participants are presented with trajectories that show their true location (true), i.e. spatially meaningful, participants are more confident in their responses as Figure 40 shows. Participants feel more confident in their response when the trajectory for the ski tour activity is in its true location (M=4.18), rather than for a false trajectory (M=3.14).

As response data are not normally distributed, a Wilcoxon-signed-rank test was applied to test whether context has an effect on participants' confidence to analyze movement trajectories. The test is based on negative ranks. The z-score is -5.011 and is significant at $p<.001$. Overall participants are significantly more confident with context information ($M= 3.38$) than without ($M= 2.33$), $z=-5.01$, $p<.05$, $r=-0.755$.

Object recognition

In the second quantitative question participants' had to identify the moving object.

Assessing the response accuracy by path type for the two context conditions, we see that participants recognize the moving object more accurately when the trajectory is presented with geographic context information (see Figure 41). Especially for the closed Tour trajectory (left most column), the difference between the two conditions is high, i.e. 25% accuracy without any context versus 65,9% accuracy with context information. However, the difference between the different activities and path types within one context condition, e.g. with geographic context, is rather small (50-65%), which suggests that neither a certain path type (open or closed) nor a specific activity leads to better performance of participants.

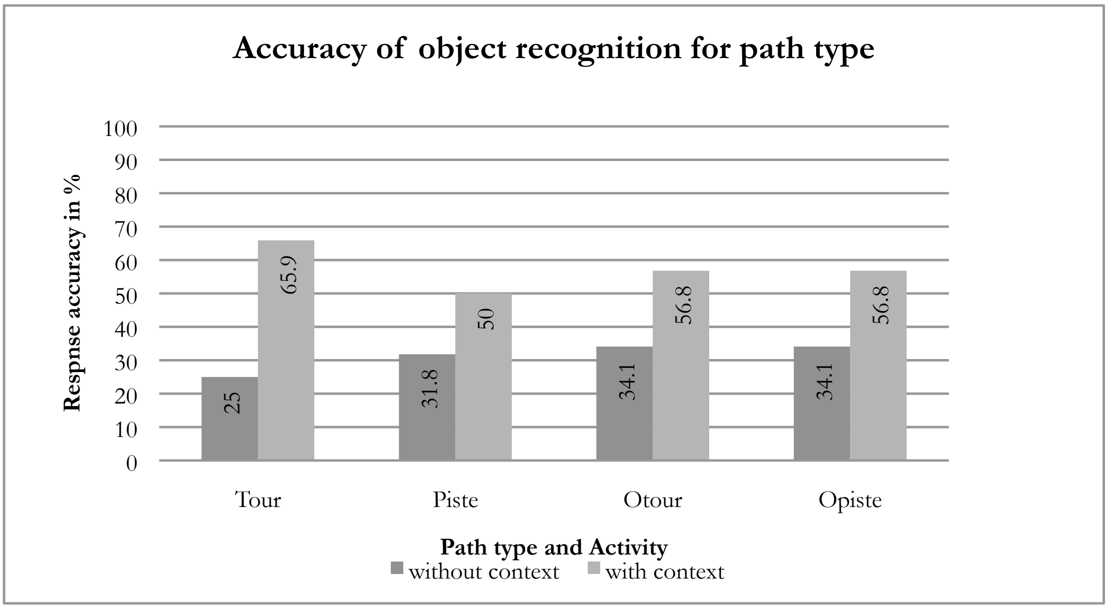


Figure 41: Accuracy of object recognition by activity and path type

More interesting is the performance of participants when aggregating the data according to context correctness, i.e. if the trajectory is presented in its true geographic location (as shown in Figure 42). The differences for the true and false piste skiing trajectories are not that obvious. For piste skiing trajectories participants perform better with context information, but no difference seems to exist between the correct and incorrect location of the trajectories. Conversely, we can see a difference when examining the ski touring data. In both cases, participants performed better with context information, but while 81,8% of the participants correctly identified the moving object in the true trajectory, only 34.1% of the participants identified the object correctly in the incorrectly placed trajectory condition. Figure 43 shows the same trajectory, in a) the correct geographic location, and b) the incorrect geographic location. A meaningful tour trajectory leads onto Piz Tarretas and back (a), while in (b) the trajectory crosses steep cliffs and does not have a meaningful start and end point. Participants therefore might have identified the trajectory to be from an animal, rather than a human. These findings suggest that context and background knowledge does matter in this instance.

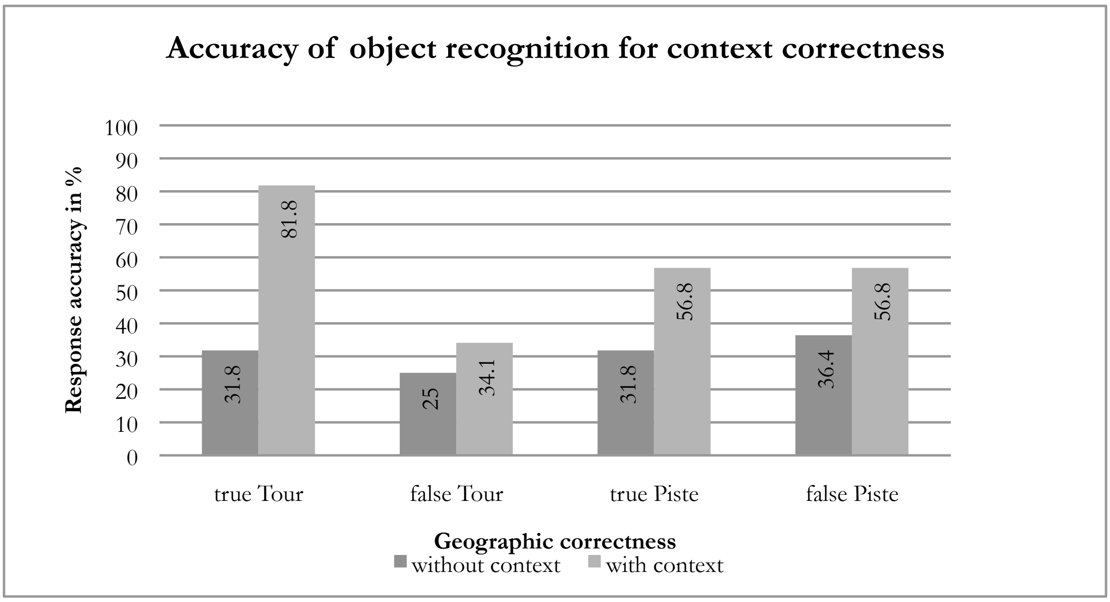


Figure 42: Accuracy of object recognition for correctness of context

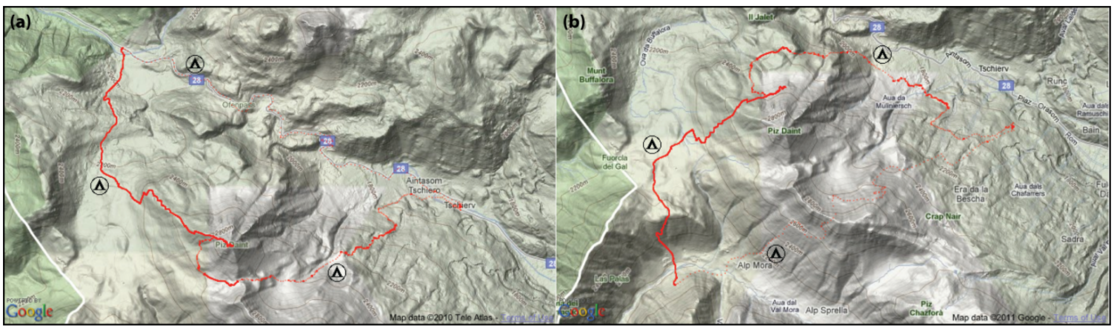


Figure 43: A correctly placed trajectory leads to Piz Tarretas (a), while an incorrectly placed trajectory (b) does not lead anywhere

To better understand why participants could not correctly identify the moving object, I briefly examine the frequencies for object recognition without context information more closely. Participants were given four choices, namely human, animal, machine, and natural phenomenon. Figure 44 shows the frequencies for all options when participants had no context information, while Figure 45 shows the frequencies of all response frequencies with context information.

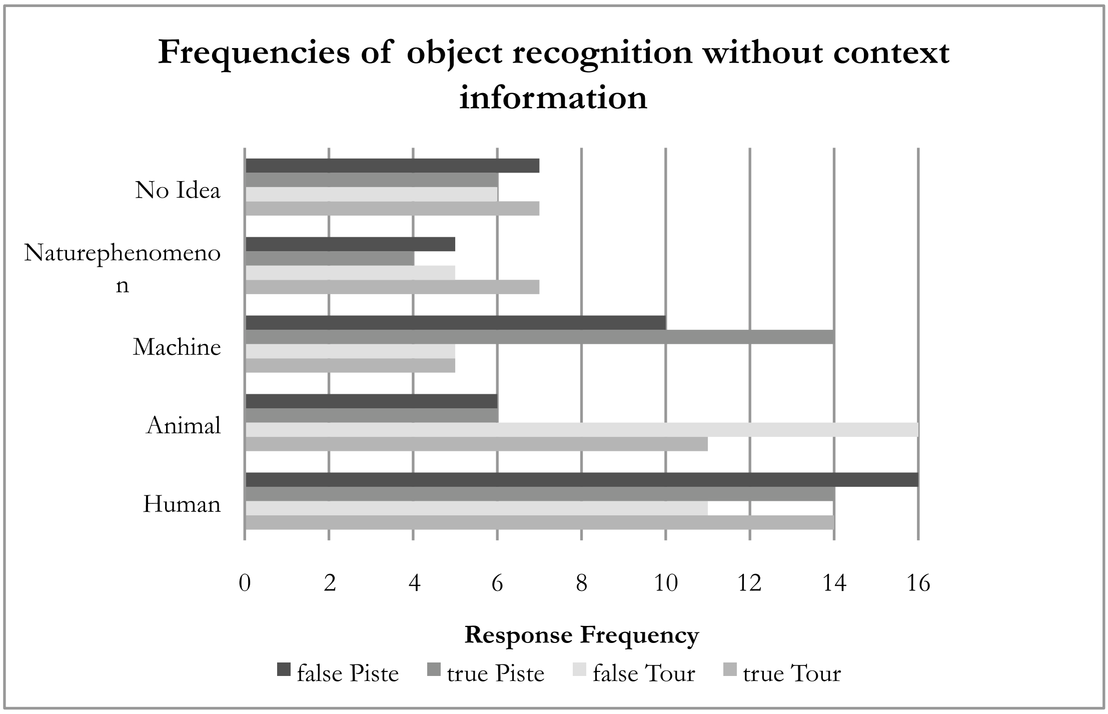


Figure 44: Frequencies of object recognition without context information

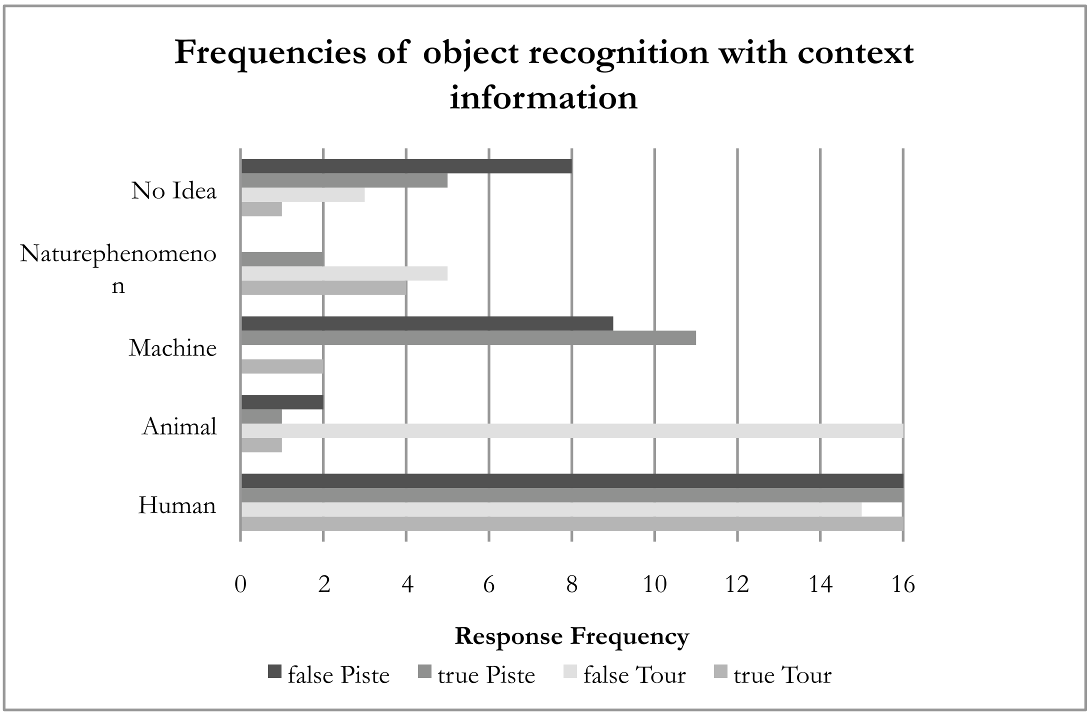


Figure 45: Frequencies of object recognition with context information

These two figures clearly show that participants identify a human as the moving object more frequently with context information than without context information for all activities. The frequencies for animal, natural phenomenon, and machine drop quite significantly when context information is provided. When presented with trajectories from skiing on slopes, most participants favor machines. The reason is, that the trajectory has straight lines, which does not appear very human. It is also noteworthy that when presented with an incorrectly placed trajectory for the ski touring activity we can observe a difference in accuracy again. In this case, most participants favored an animal to a human moving object. When related to the limited confidence when presented with an incorrectly placed trajectory, we can conclude that participants feel less sure about the object and its movement when the trajectory seems mis-placed.

A test for normal distribution reveals that the accuracy values are also not normally distributed. Therefore the Wilcoxon-signed-rank test is used. The test reveals that 31 participants were more accurate when presented with context information. Five participants scored lower when context information is provided and eight participants have tied ranks. The test is based on negative ranks. Z-scores of +/-4.267 are smaller than .001. We can conclude that accuracy increases with context information. To summarize the accuracy results for both conditions for participants' accuracy was significantly higher with context information (M=57.38%) than without context information (M=31.25%), z=-4.267, p<.05, r=-0.643.
I can briefly summarize the quantitative analysis by stating that accuracy and confidence significantly increase with geographic context information. In a next step, I will highlight the results from the open questions.

Qualitative Analysis
This section looks at possible reasons why and how the results of accuracy and confidence can be explained, by reporting the response frequencies of the specific categories (as explained in Chapter 4.2.3). I first examine the first open-ended question asking what the red path represents. Figure 44 and Figure 45 represent the frequencies of categories for ski tour data (a) without and (b) with context information. When comparing the two graphs we can see that more categories are used when no context information is provided. Obviously participants can be more specific about the meaning of the trajectory when additional information is provided. Almost all participants seem to believe that the red path must be a human or animal trajectory, or a trail, e.g. hiking trail, and not an artifact. Trail and trajectory categories both lead to the same assumption that a moving object with reasoning has left this trajectory, being animal or human.

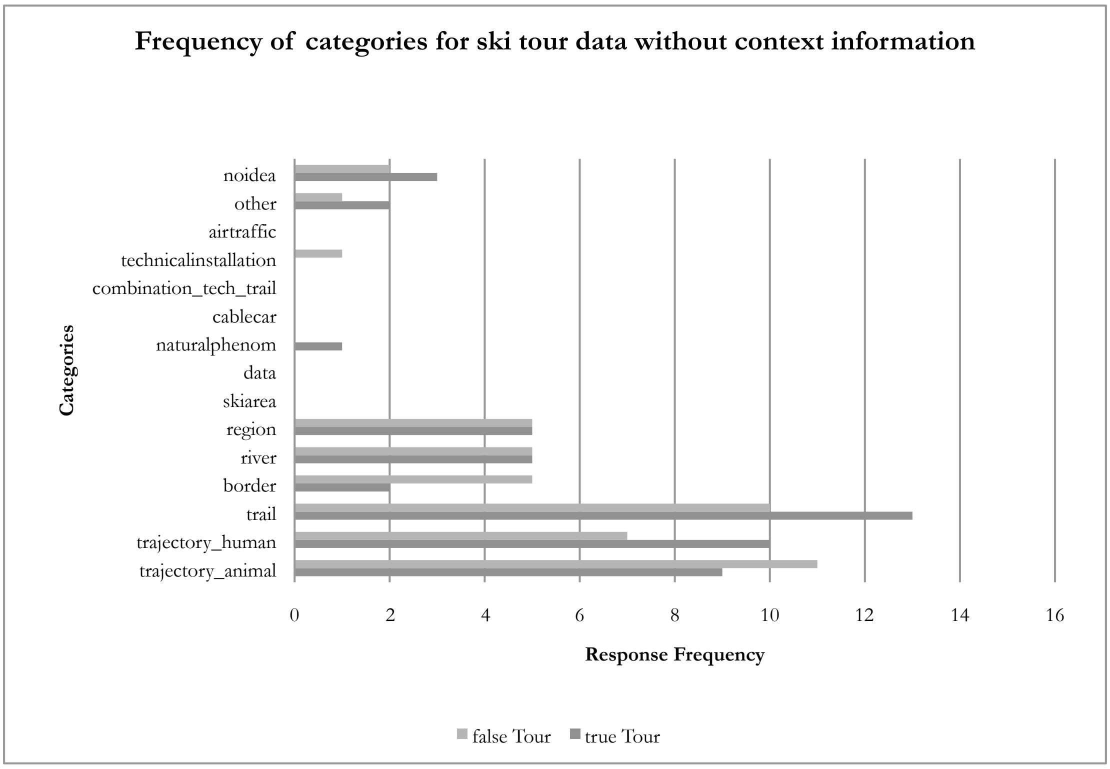


Figure 46: Frequency of categories for ski tour data without context information

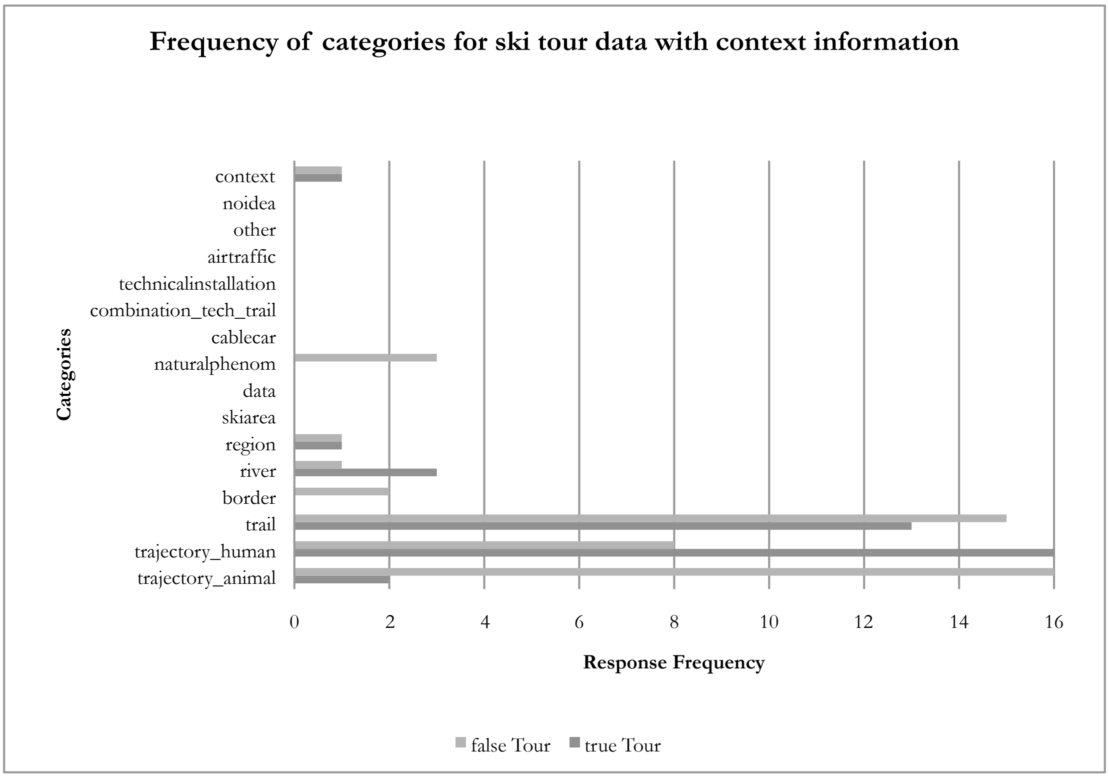


Figure 47: Frequency of categories for ski tour data with context information

A similar response pattern can be observed when inspecting participants' responses for the activity skiing on slopes data. Figure 48 and Figure 49 show the response frequencies by categories, (a) without and (b) with context information. Similar to the data about ski touring, we can see that fewer categories seem to be needed when context information is provided. Different categories are used than for ski touring data, especially categories that include some kind of technical equipment, such as ski area, air traffic or other types of non-self-propelled locomotion. In other words, when context information is provided, participants focus on the combination of movement with technical equipment. The categories cable car, combination of technical and trail, as well as ski area, are the most mentioned categories, indicating that participants not only focus on the shape of the trajectory, but also consider the geographic context in which the movement takes place.

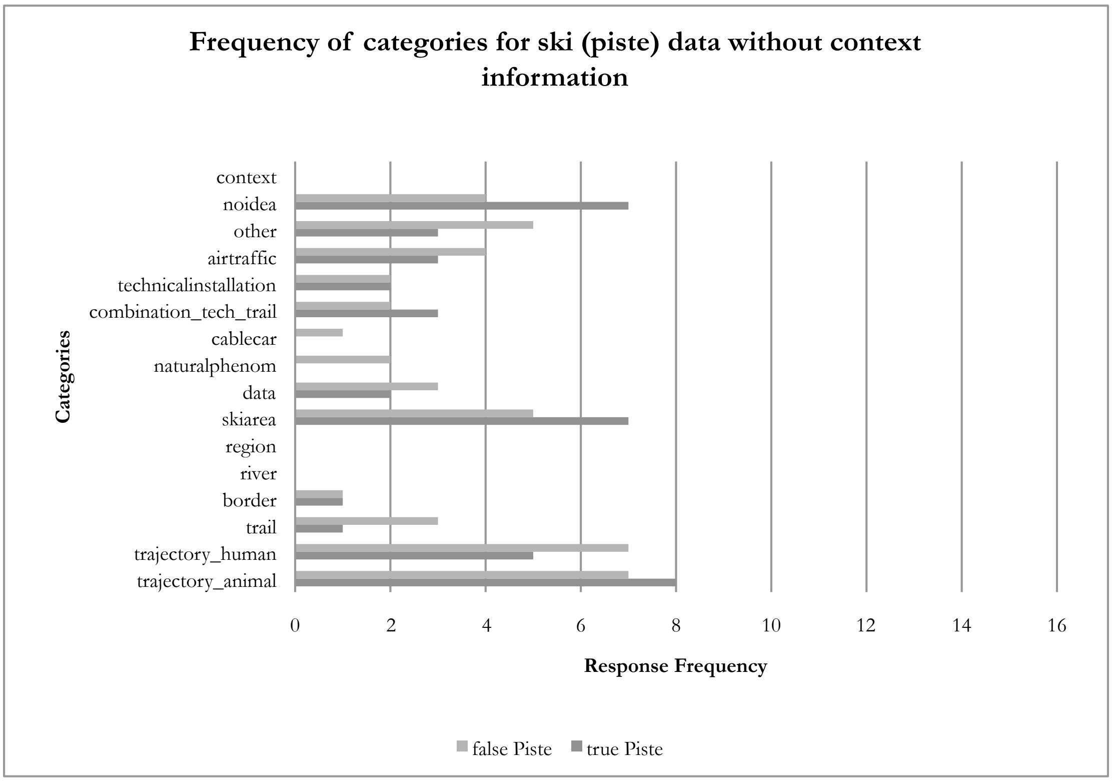


Figure 48: Frequency of categories for object recognition for skiing on slopes (piste) without context information

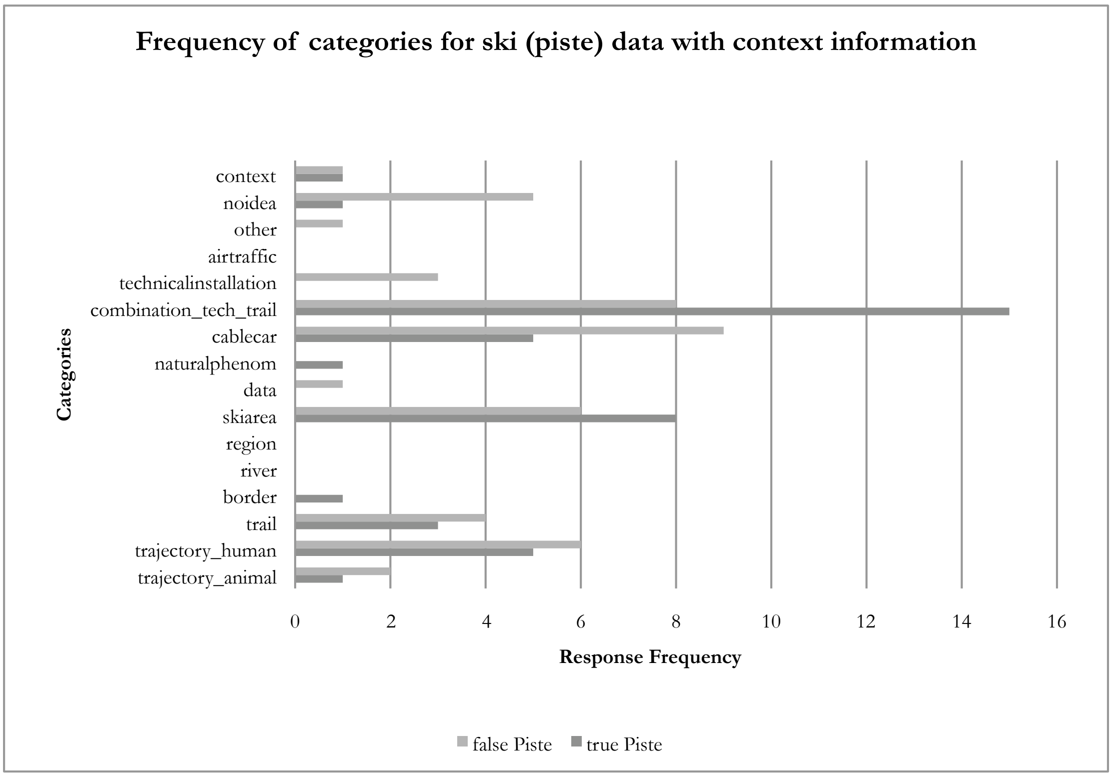


Figure 49: Frequency of categories for object recognition for skiing on slopes (piste) with context information

I now examine the results of the second open question, namely the response frequencies of the categories participants used when adding comments. Figure 50 and Figure 51 suggest participants' mention fewer, but more specific comments as compared to the previous question. When participants have context information, fewer comments are made and these are focused onto a minimum of categories. A reason for fewer comments with context information could be that the concept and reasoning about the movement trajectory gets more focused during the experiment, i.e. participants have thought about the kind of object and its behavior enough to give precise comments. The additional comments were then mainly used to explain participants' reasoning. Without context information, participants commented on many different things, mainly the path itself, i.e. its shape, the constitution of the line, its start and end points, as well as speed. The comments seem to be focused more on the appearance of the trajectory, rather than the semantics without context information.

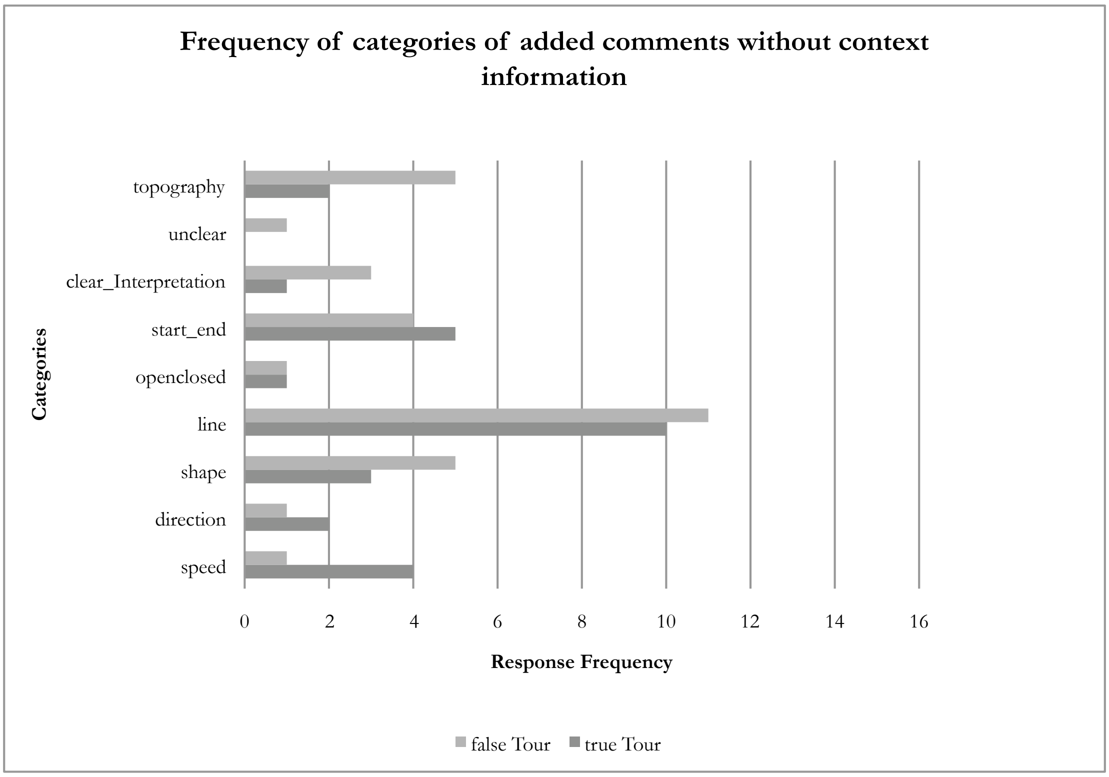


Figure 50: Frequency of categories of added comments without context information

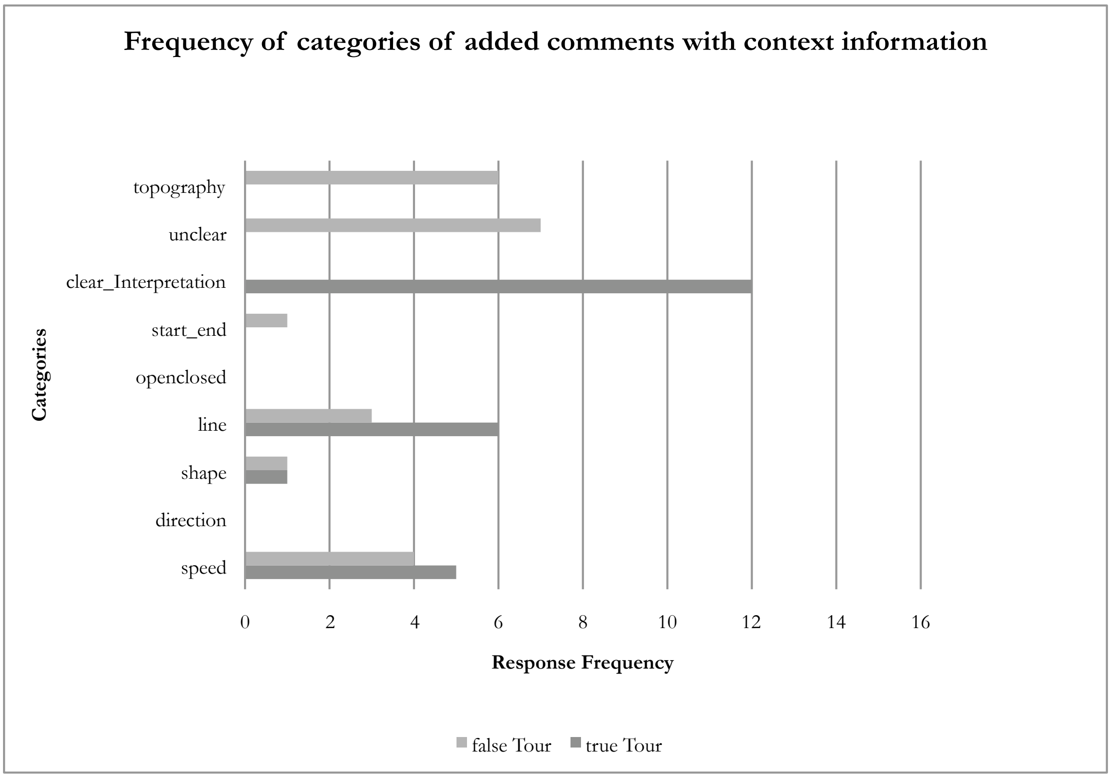


Figure 51: Frequency of categories for Tour, added comments with context information

Analyzing which categories are most common when context information is provided shows that there is a notable difference between correctly and incorrectly placed trajectories. When presented with a correct trajectory, participants focus on the speed and the line of the red path, and, most importantly, give a clear interpretation what the trajectory represents. In contrast, when the trajectory is not at its correct geographic location, participants focus on speed, the topography, and give an interpretation that reveals that participants are unsure what the path represents. Some individuals specifically state that the relation between the topography and the trajectory seems awkward. In contrast to the condition without any context information, participants now focus on the content, rather than the appearance of the trajectory and topography.

Next, I examine the results of the skiing on slopes (piste) data. We can observe an analogous trend for the skiing data. The comments of the participants in the first half of the experiment, i.e. without context information, are more diverse than with context information in the second half of the experiment (also see Figure 52). Most participants comment on the shape of the trajectory, probably due to the fact that the trajectory is distinctively different from the touring data, because it has straight and bent parts. Hardly any differences can be observed between the two trajectory conditions (correct and incorrect geographic location) when no context information is provided. On the other hand, with context information we can observe differences among participants' comments (also see Figure 53). For the correct ski trajectories (true Piste) most participants give a specific interpretation of the represented data. Some participants also comment on the shape of the trajectory and speed. However, when the trajectory is not correctly situated in the environment, most participants comment on the topography, and that the interpretation is more difficult of the trajectory. Five participants however give a clear interpretation of the trajectory, despite its dislocation in the environment.

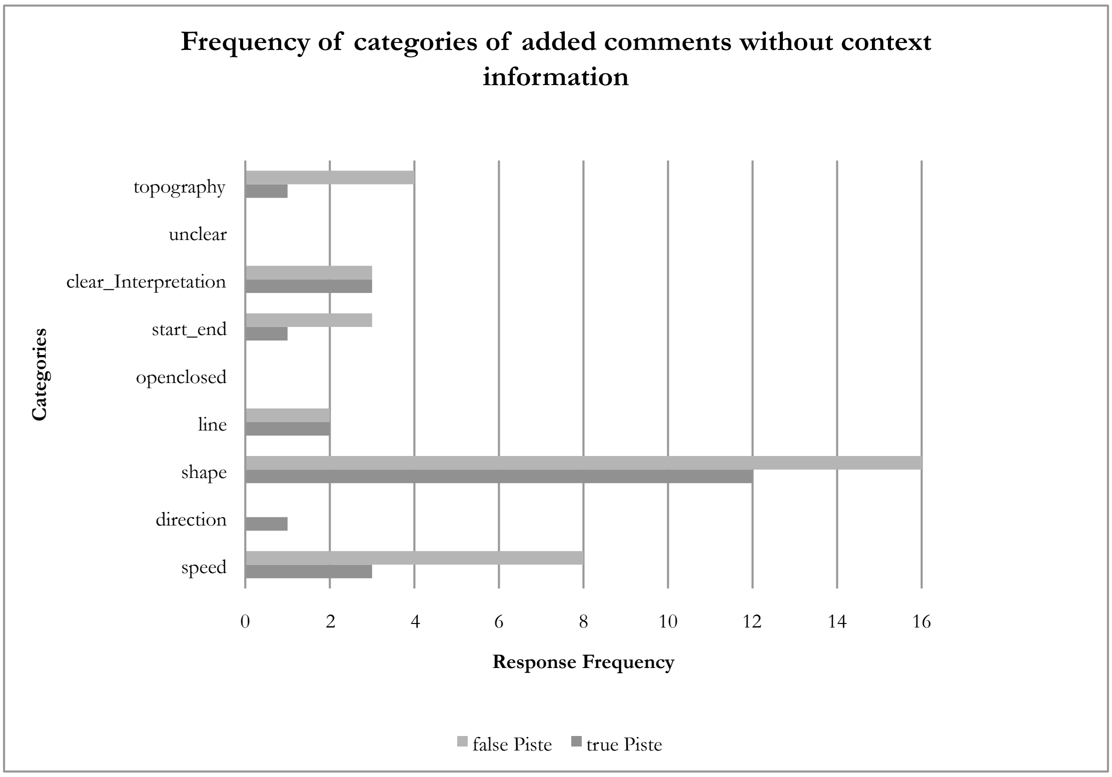


Figure 52: Frequency of categories for Piste data, added comments without context information

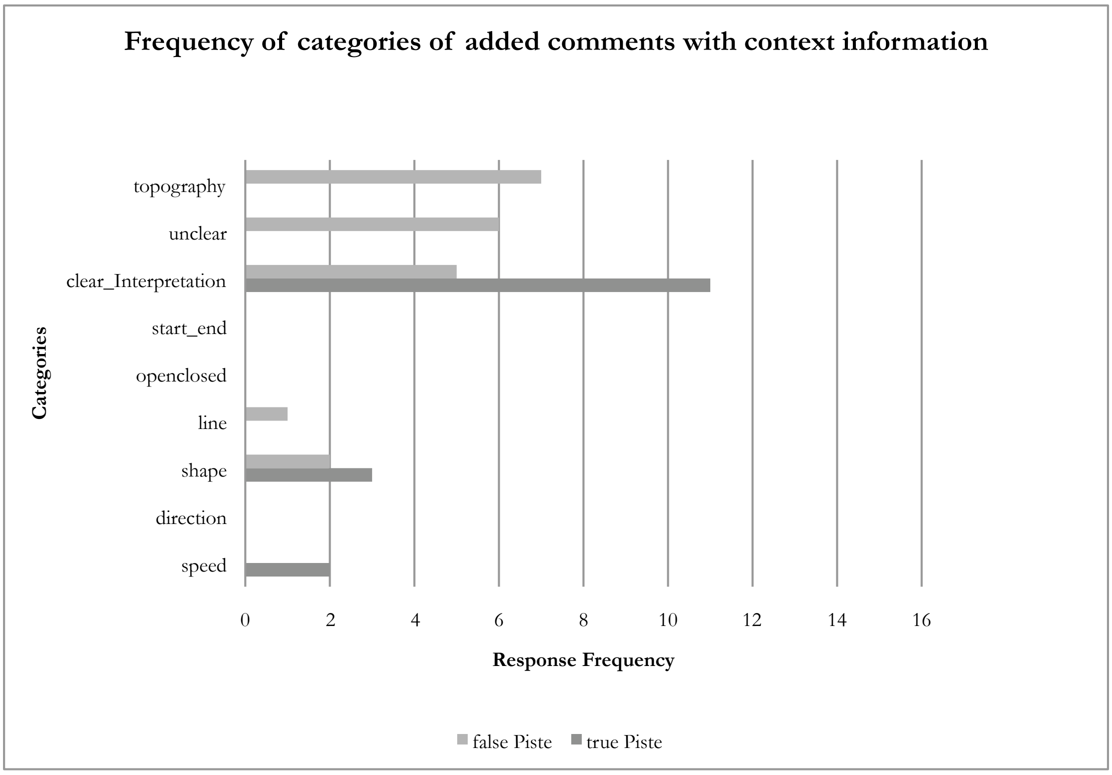


Figure 53: Frequency of categories for Piste data, added comments with context information

5.2.6 Summary of Results for Experiment II

Most participants assume that humans or animals made the tour trajectories, which is surprising, as they could have also considered natural phenomena, such as the path of a hurricane, or a border of a lake. Participants were not told at the beginning of the experiment what kind of movement data they are looking at. Especially they were not told that the trajectories were made with GPS samples. Perhaps the small Google Maps logo displayed in the corner of the display might be responsible for this result, and participants assumed humans or animals making the trajectory. It is also interesting to note that most participants stuck to their ideas about the moving object and its behavior during the first part of the experiment. Most participants used consequently one explanation for the tour trajectories and one explanation for the piste trajectory and only changed their explanation with the added context information in the second half of the experiment.

The analysis of the categories, found in the qualitative questions, reveals that precise interpretations were given with context information. Specifically, more participants interpreted the red path as a human trajectory when context information was provided, as opposed to landscape features or animal trajectories without context information.

Table 2 highlights the most important effects shaded in red (strong differences) and orange (slight but noteworthy differences) colors.

Table 2: Summary of results for Experiment II

		Confidence (from 1-5)		**Accuracy (in %)**	
		No context	*With context*	*No context*	*With context*
Behavioral context	*Tour*	2.43	3.65	28.5	61.3
	Piste	2.29	2.97	32.9	53.4
Path type	*Open*	2.37	3.07	34.1	56.8
	Closed	2.35	3.69	28.4	57.9
Correctness	*Correct*	2.46	3.71	31.8	69.3
	Incorrect	2.26	3.06	30.7	45.4

Behavioral context, i.e. different activities of movement, does not significantly influence participants' response accuracy and confidence. These results reflect in the quantitative questions, but not so much in the qualitative questions. When identifying the red path, participants made a distinction between the two activities. For tour trajectories most participants considered it human or animal, as opposed to piste data where most participants considered it to be made from machines. The reason is potentially the shape of the path, as it is more irregular for the activity tour. In contrast, trajectories from piste data have straight lines, which seem untypical for natural phenomena or processes. These findings correspond to the answers in the additional comment question, where most participants' commented on the particular shape of the trajectory, especially the straight lines when adding comments to the piste data displays. For tour data, most participants commented on the character of the line, i.e. if dots were visible or how thick the line was. The path type did not reveal any significant differences for accuracy and confidence and therefore did not influence participants' ratings and/or comments. However, the experiment results indicate that it is more important what the shape of the line looks like, i.e. straight lines vs. bent lines, rather than open or closed trajectories. The results therefore indicate that path type or appearance of the trajectory plays a role, but not as predicted.

One interesting effect can be observed when the trajectory is not presented in its true location, but is 180° reflected. Participants chose more often that the moving objects are animals, rather than humans, if the trajectory was not at its true location. A potential explanation for this effect is that incorrectly located trajectories cross steep terrain, and participants probably concluded (rightly) that humans cannot traverse this kind of terrain. In case of the piste trajectories the lines are crossing a valley, which is also rare in reality. Since most participants assumed these trajectories to be from skiing activities, these trajectories also were not sensible. These results are highlighted in the accuracy and confidence results in Table 2.

In the second experiment I was able to demonstrate that accuracy and confidence of participants increases when a movement trajectory is presented with additional, geographic, context information. It basically tells us that people are more confident when making judgments about movement trajectories with context information, and their performance increases.

To conclude, I answer the following two research questions, as posed at the very beginning:

> **Q2a:** Are participants more accurate and confident to identify a moving object and its behavior with geographic context information?

Yes, participants perform more accurately when presented with context information to identify the moving object than without context information. The confidence of the participants also increases with additional context information.

Q2b: Does it matter for the identification of moving object and its behavior if a movement trajectory is situated in the correct geographic context?

Yes, it does matter if the trajectory is situated in its true geographic context, because we have seen a decrease in accuracy and confidence when presented with incorrectly located trajectories.

5.3 Experiment III – segmentation

The first two experiments have revealed that context matters for the identification of moving objects and their respective behavior. However, context is not relevant for the identification of movement parameters as the first experiment showed. The third experiment examines how humans segment static 2D trajectories of movement data and to see whether the segmentation by humans can lead to similar results as existing computational approaches. The second goal of this experiment is to identify if geographic context information is making a difference for participants to segment the trajectory. Thus, it is aiming to clarify if generic and behavioral movement patterns would require different computational approaches for the analysis of the trajectories, as suggested through the separation of generic and behavioral patterns in the taxonomy of movement patterns (Dodge et *al.* 2009). The experiment has two main research questions:

> **Q3a:** Are participants segmenting the movement trajectory according to the basic movement parameter when no geographic context is provided?
>
> **Q3b:** Are participants segmenting the movement trajectory based on activity changes, when geographic context information is provided?

5.3.1 Participants

A total of 50 participants finished the experiment, 32 male and 18 female. 24 participated without context information, and 26 participated with context information. The experiment was conducted at three different locations. One third of the subjects participated at the University of Twente, at the faculty of ITC in Enschede, the Netherlands and were students of the graduate module "use, users and usability". Additionally, fourteen graduate students participated at the Institute for Geoinformatics (IFGI) at the University of Münster, Germany. The remaining participants were students and researchers from the Department of Geography at the University of Zürich, in Switzerland.

Two participants were removed from the analysis, because the task ("segmentation into the largest meaningful units") was not entirely understood. This showed in the segmentation of the trajectories, which was high above average. The analysis is therefore performed with 17 females, and 31 male participants, i.e. 48 participants in total. 22 participants had no context information during the experiment, and 26 participants had geographic context information. Most participants are (very) familiar with Google Maps (95,9%) and also have worked or used GPS devices before (77.1%).

5.3.2 Experimental Design

The independent variable of this experiment is geographic context information. The identical data set used for Experiment II (see Chapter 4.2.2) was also used for the set-up of this experiment. In contrast to the previous experiment, however, we use a between-subject design, i.e. students either perform the segmentation without any context information, or with context information. Each participant had to segment all 16 movement trajectories, as listed in Table 1 on page 69. The segmentation task follows prior work by Zacks (2004) where participants segmented animated displays of moving entities. In our study, participants respond by placing circles for the segmentation on the depicted trajectory into the Google Maps API display. We use circles for two reasons: First, we would like to capture when something has happened, such as a change of direction, rather than splitting this particular moment up. Second, we would like to make sure that the data is easily analyzable even if participants do not hit the exact same location (coordinate wise). In the remainder of the thesis we use the terms breakpoints or segmentation points synonymously to describe the placement of circles by the participants.

The technical design of the experiment is slightly more complex than the preceding experiments, because participants are not presented with an online questionnaire but are asked to draw circles into the display to segment the shown movement trajectories. Google Maps API and JavaScript were used to display the trajectories and to allow the drawing of circles. For each stimuli, two files are important, namely a *.php file (as an example called track.php) that each stimuli has individually and a general functions.js file. The track.php file opened the stimuli and task that participants had to do. It also provided the radio buttons to allow circles to be drawn, and contained another question regarding participants' confidence.

In total 64 track.php files were generated, 32 stimuli without any context information, and 32 stimuli with context information. From the two sets of 32 displays, I generated two identical sets of 16 stimuli, but in a different order. The order of the series was determined by a random number generator (www.random.org). I therefore had four sets of experiments (Experiment_C1, Experiment_C2, Experiment_H1, Experiment_H2), which the experiment leader assigned randomly to each participant. C1 and C2 are with context information, while H1 and H2 are hiding geographic context information. The experiment was implemented on a server at the Department of Geography and was tested in pilot experiments multiple times. The full JavaScript code and the code for one of the stimuli can be found in the Appendix of this thesis.

The experiment was administered on personal computer with a standard Windows XP interface on a 17-inch color display. The screen resolution was set to 1280x1024 pixels. The experiments in Enschede and Zurich were conducted in a small office space, and in an empty computer lab at the University of Muenster.

5.3.3 Procedure

Each participant was tested individually. The participants were welcomed and thanked upon arrival at the experiment location. After being seated in front of the computer, participants were introduced to the test set-up and instructed that they only need a mouse to do the experiment and that the experiment website sometimes needs a few moments to load the next page. Participants were asked to submit each response only once and be patient for the next stimulus to appear. They were not able to see the browser bar at the top of each browser, as it contained relevant information about the stimulus. The experimenter was present during the experiment and available for clarifying questions and potential technical issues.

A welcome screen explained the participant what the experiment is about and that it is part of a dissertation project. Also, they were informed about the data collection and that the information obtained will be kept anonymously and confidential. In a next step, before starting the actual experiment, participants were introduced to the interface by a demo to familiarize themselves with the display. During the demo, questions were answered to clarify the task and to explain how the drawing of the circles work if necessary. Once the participants felt familiar with the display, they proceeded to the actual experiment.

The participants of the experiment are presented with digital trajectory displays and are asked to intuitively segment the trajectory into the largest units that are natural and meaningful to them. Figure 54 shows the display with the task participants are presented with and shows how specific areas of the trajectory are segmented by the circles. After the segmentation task, participants are asked to rate their confidence on a five-point Likert Scale (Tastle and Wierman 2006) ranging from very confident (5) to very unconfident (1). All participants segment 16 trajectories, before answering demographic questions. I have asked participants about their sex, age, their familiarity with Google Maps and if they have worked with GPS data before. At the end of the experiment, participants were thanked for their time and effort.

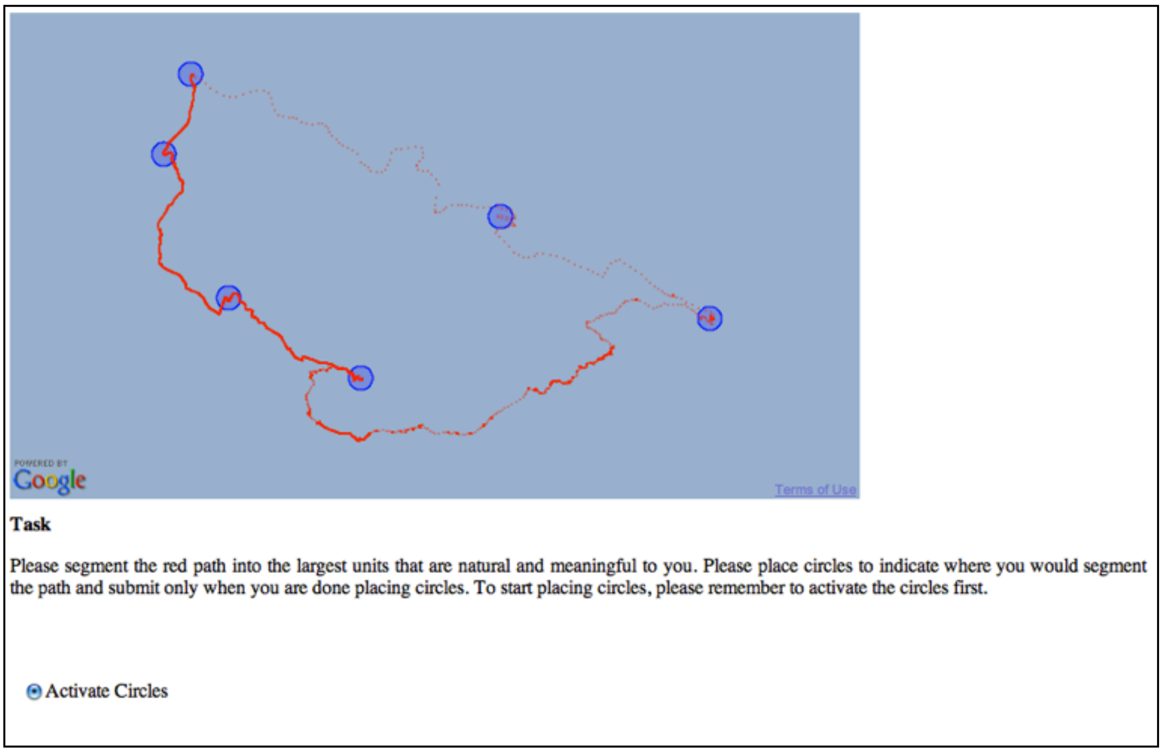


Figure 54: Experiment display showing the task and identifying trajectory segments

5.3.4 Data Preparation

In total 50 participants finished the experiment, having drawn a total of 6695 points. The workflow of the data preparation is depicted in Figure 55 and will briefly be described in the next section.

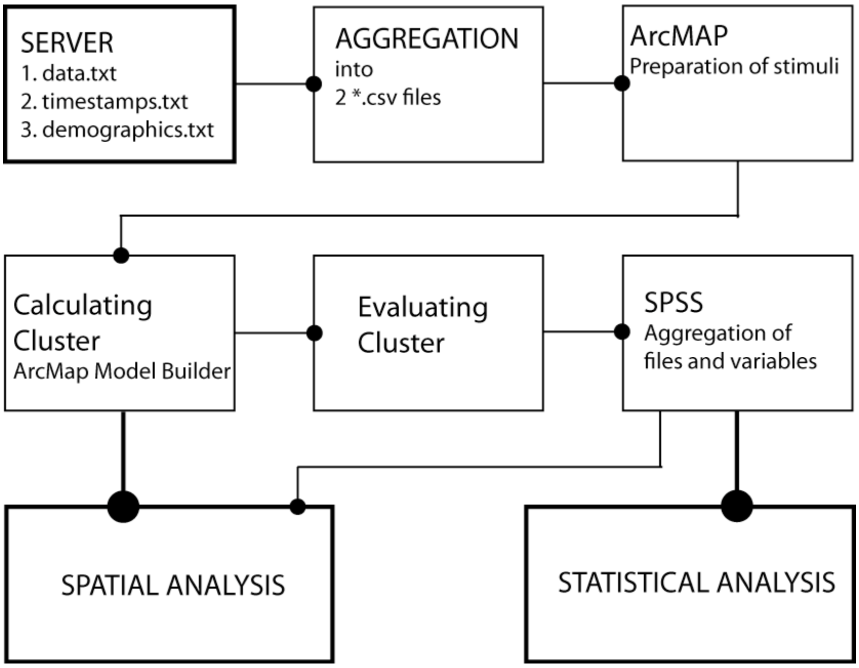


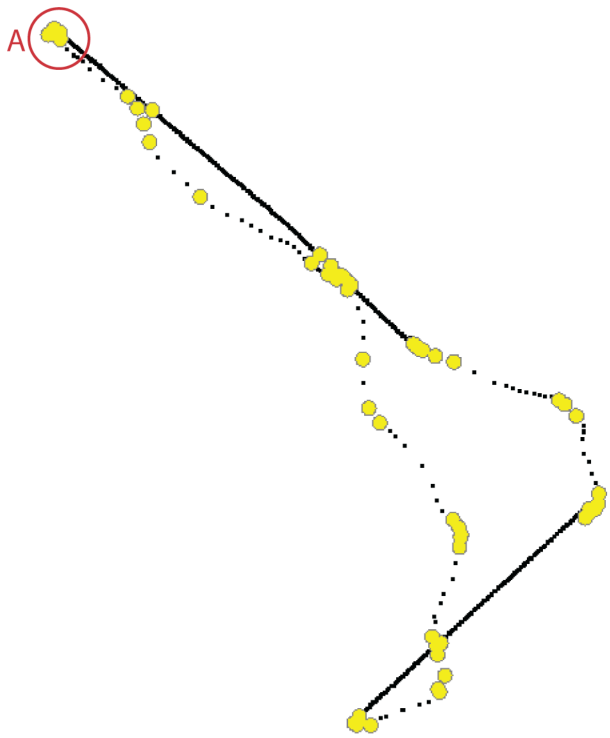
Figure 55: Data Preparation for Experiment III

Collected response data of the experiment was stored on the server, with one directory for each participant. Each directory included three text files, namely timestamps.txt, data.txt, and demographics.txt. The timestamps file contains the start and end times for each stimuli, i.e. when the participants started to segment the trajectory and when the submit button was pressed. Demographics.txt included the answers to the four demographic questions. The most important file is the data.txt, which includes the sequence for all circles drawn for each stimulus per participant and the coordinates of each drawn circle. In a pre-step all pilot experiment files were deleted. The training of the participants with the demo did not generate any files. For all other files a cross-check was made if the start and end times of the experiment match the start and end times noted down by the experiment leader. The coordinates of the trajectories and of the drawn points from the without context condition were re-transformed to its original location (as the trajectories were displayed in the ocean instead of the mountains) to be able to spatially compare the segmentation points of both context conditions. The next data preparation step included the aggregation of many user files into two large *.csv files data with a small python program. The first file, called datatable.txt, contains the following: filename, stimulus name, start and end times from the timestamps.txt, the coordinates of the points, and a value for participants' confidence. The filename basically represents the participant name as each participant generated a folder with its own sequence of letters and numbers, e.g. 4c2a0f3c8d0ff. A second file contains the filename, as well as the demographic data from the demographics.txt. The datatable.txt file could then be

imported to ArcMap to graphically display the results. Initially, the representation of the data was quite cluttered and crowded due to so many points, but sorting the data according to the stimulus name and then creating layers for each stimulus helped to display only the relevant data for each stimulus. The camp symbols were also loaded into ArcMap again to compare context information to the drawn circles.
Calculating clusters for each stimulus out of the points was an important step to identify and compare the number of circles spatially and to prepare them for the statistic analysis. The ArcMap model builder (Figure 50) was used to generate the clusters. The model consisted of multiple steps, and is described in more detail in the appendix. Buffers were created around the circles with a width of 25m. Other thresholds were tried with 10m, 50m, and 100m but did not deliver valuable results. With a 10m threshold, for instance, each point was marked individually, while with 100m all points were connected to a single cluster. The 25 m buffer seemed also appropriate to the resolution of Google Maps, i.e. the spatial resolution available for this area. The buffer was necessary to compensate for the fact that participants would place the circle at the same spot, but probably will not hit the exact same coordinates.

What I wanted to find out is participants' reasoning for the segmentation of trajectories. I therefore look at the most common clusters and evaluate which criteria participants have applied based on the added comments from Experiment II to identify possible criteria. The criteria I used for the evaluation were three generic and three behavioral categories. The generic categories were change of direction, change of speed, and spatio-temporal complexity, while the context categories are change of altitude, camp symbols, and a change in activity. Change of speed meant if the speed was changed visibly, i.e. if the trajectory got thicker and the line showed more points. Spatio-temporal complexity means when the trajectory intersects at a point, which happened mainly in the piste data, or if the trajectory changed the direction in short intervals. Change of altitude means if speed and direction did not change, but a point was made where the map indicated a steep cliff. This category could only be measured for the participants with context information and basically only happened when the trajectory was not located in its correct geographic context. The category camp symbol stands for all points that were made next to a camp symbol and change of activity means an obvious change, such as the difference between riding a ski lift and skiing, as well as hiking up, skiing down, or using the car in the tour data (if available). Change of activity was coded for both conditions, because the trajectory looked different in both conditions and suggested a change of activity, even though participants without context information could not infer the actual activity from the topographic map. All categories were added to the tables as new attributes.

Evaluating all clusters would not have made sense, as I want to identify a main trend of reasoning participants might have. I therefore calculated a threshold to categorize only relevant clusters. To find the threshold I calculated the mean for the frequency of points per cluster. I then evaluated all clusters where the frequency of points was larger than the mean. With this method all stimuli were evaluated according to an individual mean, i.e. a specific mean for each stimulus. This is sensible, because some trajectories are longer than others and therefore also have completely different mean number of points and thus a different mean of points per cluster. I coded the clusters based on the mentioned categories with 1 when the category was true for this cluster, and 0 if it was false. As an example, imagine cluster A in Figure 56. At this point, we can clearly see the activity changes (from ski lift to ski), the direction changed (almost 180°), and the speed changed (from a thick line to a dotted line). We cannot identify a change in altitude (at this particular point), nor specific spatio-temporal complexity (no intersections or other), nor are camp symbols at this point (not visible in this representation, but camp symbols never appeared at turning points, as described in the section before). I therefore coded the table in Figure 51 with 1 1 0 0 0 1.



Change_dir	*Change_speed*	*Complexity*	*Change_Alt*	*Camp*	*Change_Acti*
1	1	0	0	0	1

Figure 56: An example of evaluating clusters

Once the evaluation of the clusters is done, the table is joined with the larger total_ data table through the variable cluster. The joined table is then exported as a dbf to be able to open it later in SPSS.

The next data preparation steps are all done in SPSS and are mostly necessary for the statistical analysis of the experiment. First of all, the *.dbf's are opened in SPSS and all individual stimuli tables are joined to one large data file by adding cases. Context was added as a variable and was coded 1 if the stimuli were seen with context information, and 0 if the stimuli were seen without context information through a simple SPSS syntax file. The data was then aggregated in four different files, namely track_cluster.sav, confidence.sav, movementparameters.sav, and track_pointsperpers.sav, to allow analysis according to four main foci (for comparison see Table 3).

Table 3: Aggregated data files and their analysis focus

File	**Analysis Focus**
Track_cluster.sav	Number of clusters, points per cluster
Track_pointsperpers.sav	Number of points per person, per stimulus
Movementparameters.sav	Number of points per category of movement parameter
Confidence.sav	Confidence for each stimulus

The track_cluster.sav file allows the analysis of the number of clusters for each stimulus, the mean, minimum, and maximum number of points per cluster for each stimulus, as well as the number of points for each cluster. The track_pointsperperson.sav was generated to focus on the number of points for each stimulus, and the mean, minimum, and maximum number of points per person per stimulus. The movementparameters.sav holds the number of points that were placed for each category. The confidence.sav aggregates the data according to the participants and allows analyzing their confidence ratings for each stimulus.

Finally, to make the different stimuli comparable, they also had to be recoded. For example, Tour1 from the two conditions with context information, as well as from the two conditions without context information, had to be aggregated into a single variable, called Tour.

With these data processing steps, I have prepared the data for a spatial analysis with ArcMap, as well as statistical analysis with SPSS. In the next section, I highlight the results of the statistical analysis before highlighting some spatial characteristics.

5.3.5 Results of Statistical Analysis

The next section reports the results for the points per person made for the stimuli.

Similar to Experiment II, I have also calculated the differences in means depending on the correctness of spatial reference, i.e. if the trajectory is located at its correct geographic location, or if it is placed incorrectly in the environment (for explanation, see Chapter 5.2.4). In this case, the path type is not considered, i.e. a positive tour can be an open or closed path as long as the trajectory is correctly placed. The mean number of points per person and stimulus does not differ very much between the different conditions (compare to Figure 57). The results indicate that the only significant difference is with true, i.e. correctly placed piste data from skiing on slopes.

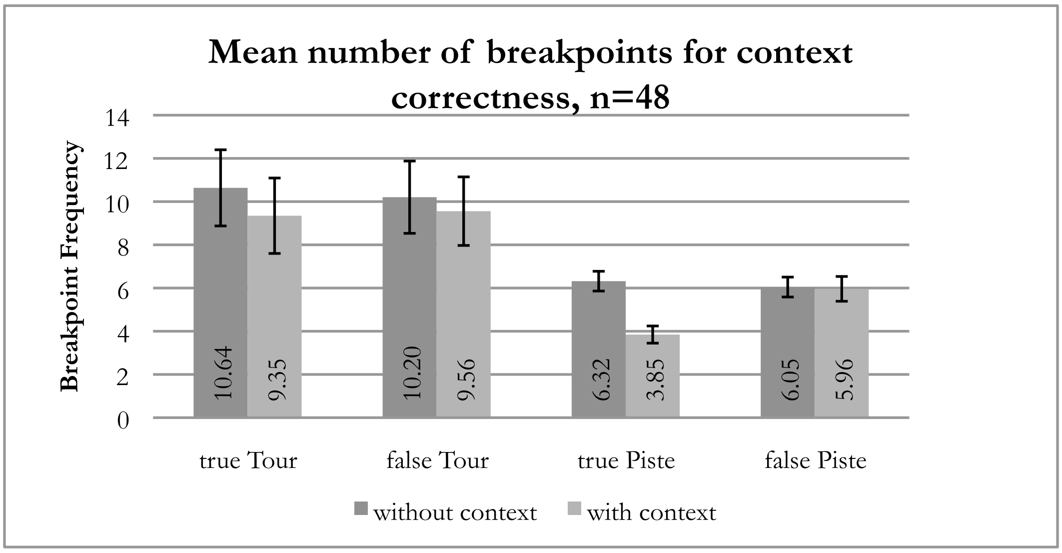


Figure 57: Mean number of breakpoints for correct geographic context

After an initial exploration of the data, I found that the data is significantly non-normally distributed (significance value .00, $p<.05$). The mean number of points that participants have drawn per trajectory is 8.36. Looking at the histogram (Figure 59) and the box plot (Figure 58) reveals two outliers, with a mean of 44.19 and 23.81 points per trajectory. As mentioned earlier, these participants were deleted from the analysis (as explained in Chapter 4.3.1), because the task was misunderstood (i.e. segmenting the trajectory into its largest meaningful units).

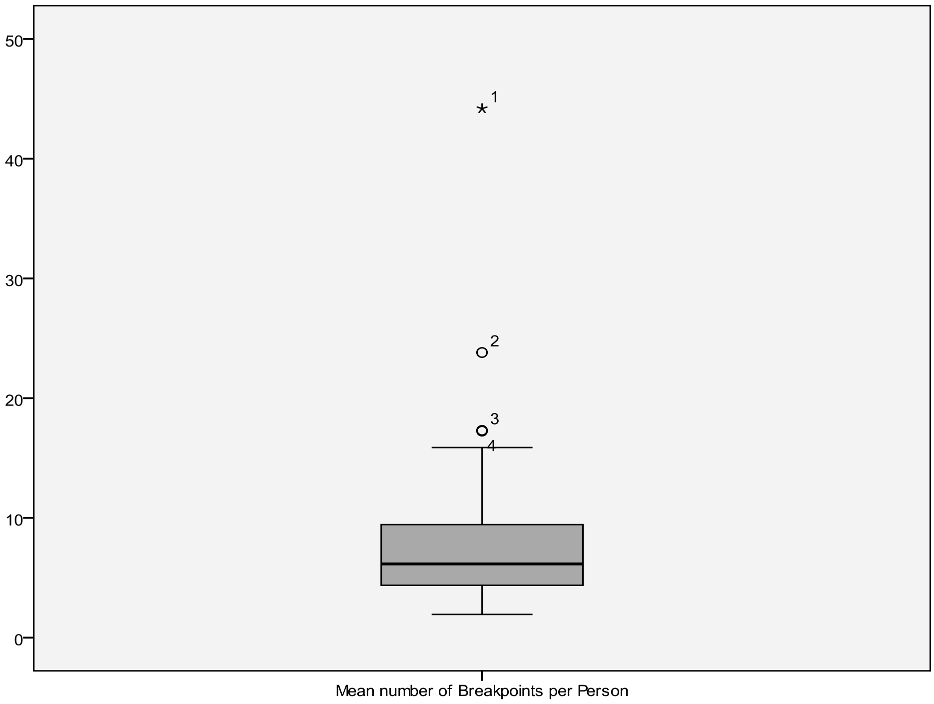


Figure 58: Box plot with two outliers for 50 participants showing the non-normal distribution

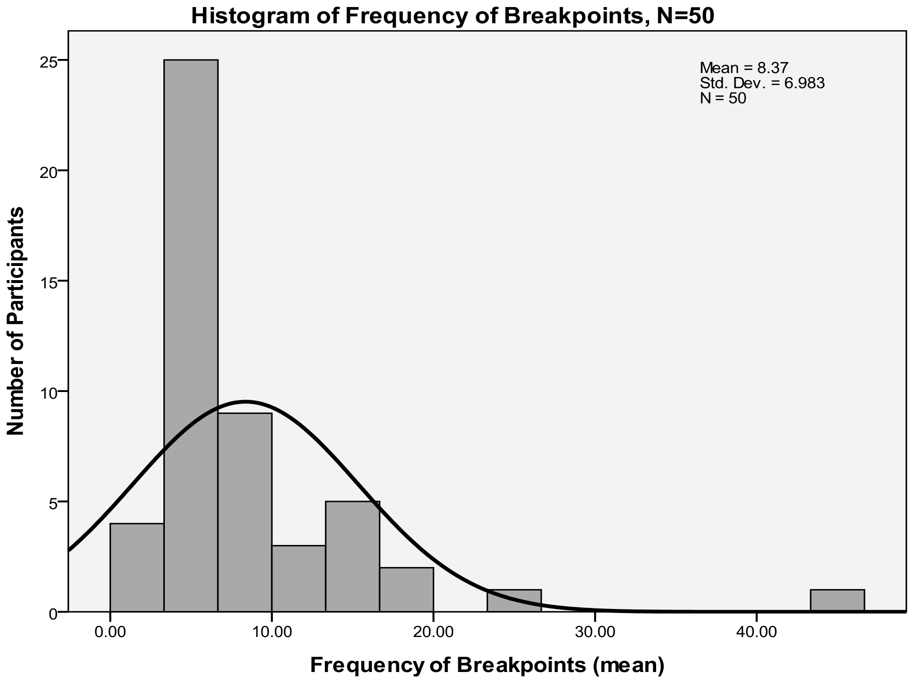


Figure 59: Histogram of the non-normal distribution for 50 participants

A test for normality with 48 participants confirms the suspicion that the data is still significantly non-normal with significance of .00. Splitting the file according to context, hoping that this causes the bimodal distribution, also showed that the data is significantly non-normal. The histogram (see Figure 60) shows the bi-modality of the data.

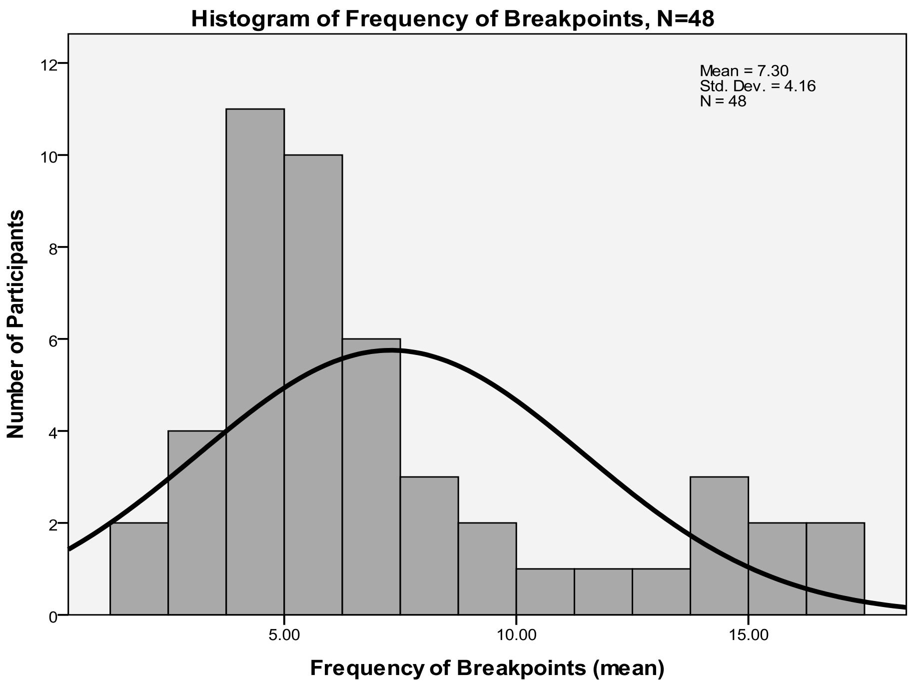


Figure 60: Data distribution of number of points for 48 participants

The bi-modality of the data does not allow parametric testing. Several approaches have been tested to understand why the data is bi-modally distributed. I have split the file according to all demographic characteristics, such as gender, age, the familiarity with Google Maps, as well as the usage of GPS data. None of these factors seems to explain the bi-modal distribution of the data.

Another possibility to understand why the data is bi-modally distributed is to find any response commonalities among all participants with a mean number of points larger than 10 (i.e., where the bi-modality of the data starts), which are ten participants. Eight of these participants were assigned to the first sequence/order of the experimental stimuli, thus starting with Tour 1. Tour 1 is the largest trajectory and also shows most changes of speed and direction. Starting with the longest trajectory possibly influenced participants' segmentation in successive trajectories. That said, it obviously did not matter which context condition was applied, because out of these eight participants, four were from the condition without any context information, and four were with context information.

I also tested how large the influence of this bimodal distribution was by running the analysis without these ten participants. A test revealed a significantly normal distribution (sig .688) for this data. A one-way analysis of variance (ANOVA) was calculated to assess if context influences the segmentation of trajectories. The ANOVA reveals that context is not significant, $F(1,37)=1.726, p=.197$. This result means, that even with a normal distribution and a parametric test, context does not matter for the segmentation of the trajectory, as the mean number of points for both conditions is not significantly different. The mean number of points without context information is 5.86 points and with context information is 5.05 points per participants per stimulus with only 38 participants.

Splitting up the entire file according to the sequence of the stimuli, i.e. ContextA versus ContextB, does not make sense for several reasons: First, there are no significant results for context in the ANOVA, even if the data was normally distributed. Second, when examining the ten participants responsible for the bi-modality it becomes obvious that they were distributed equally among the two context conditions. And third, splitting the file would mean that we do not even have twelve participants for each condition, i.e. per context per sequence, which is not a large enough sample for an ANOVA.

Since the data is not normally distributed, we run a non-parametric test, in this case the Kruksal-Wallis test, because the number of participants for each condition is now a little less than 25. The test is not significant for context with F(1).585, p<.05 (significance .444). Having context information therefore does not matter when segmenting a movement trajectory. The mean results are 7.53 points per stimulus for the condition without context information, and 7.11 points per stimulus for the condition with context information. A Kruksal-Wallis test examines whether any differences appear for behavioral context or path type. The test reveals that the means for neither activity, nor path type are significantly different, with the following significance values: Tour=.331, OTour=.534, OPiste=.305, p<.05. Only for the activity skiing on slopes (Piste) can we find a significant difference, .020,p<.05. Figure 61 confirms these results as we can see hardly any differences for the activities (either tour or piste) and path types (open stimuli are coded with O) when presented with or without context information (also see Table 14 for comparison). The activity tour, for instance, has a mean number of points per stimuli of 10.42 without context information, and a mean number of points of 9.45 with context information.

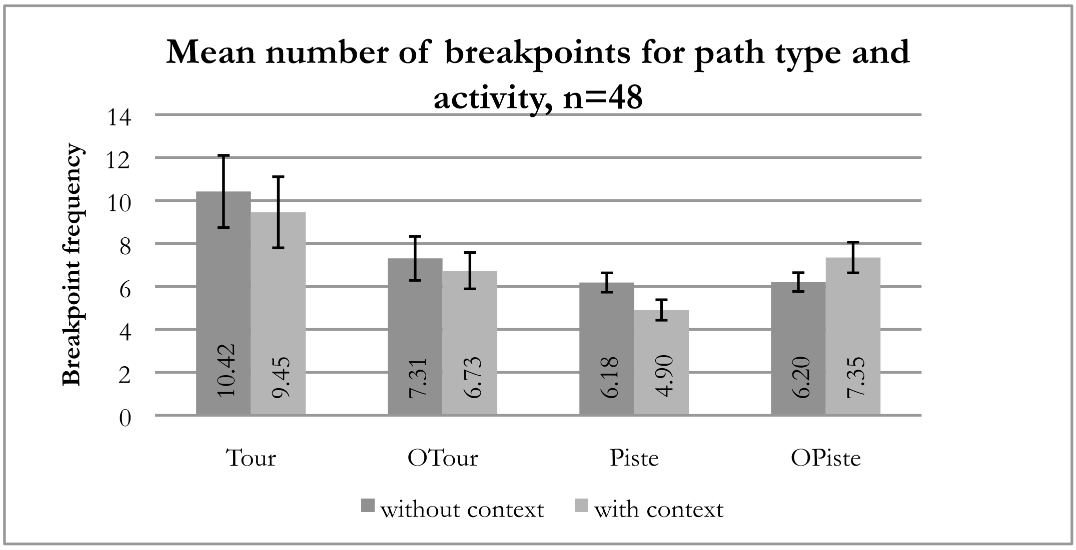


Figure 61: Mean number of breakpoints for activity and path type

I therefore conclude that context does not matter for the segmentation of movement trajectories.

Confidence

Next, I report the results of participants' confidence ratings. Confidence had to be rated on a five-point Likert scale, in which one means very unconfident or very unsure and five means very confident with their segmentation of the trajectory.

Surprisingly, confidence decreases with context information. The grand mean for confidence without context information is 3.69, while the grand mean with context information is 3.51. However, the difference is not significantly high.

Figure 62 compares the confidence means according to activity and path type and shows that there is hardly a difference visible between the two context conditions, i.e. with or without geographic context information. There are almost no visible differences between the activities (tour and piste), or between the different path types, such as open piste and piste. In other words, the behavioral context (i.e activity) and the path type do not influence the segmentation of movement trajectories.

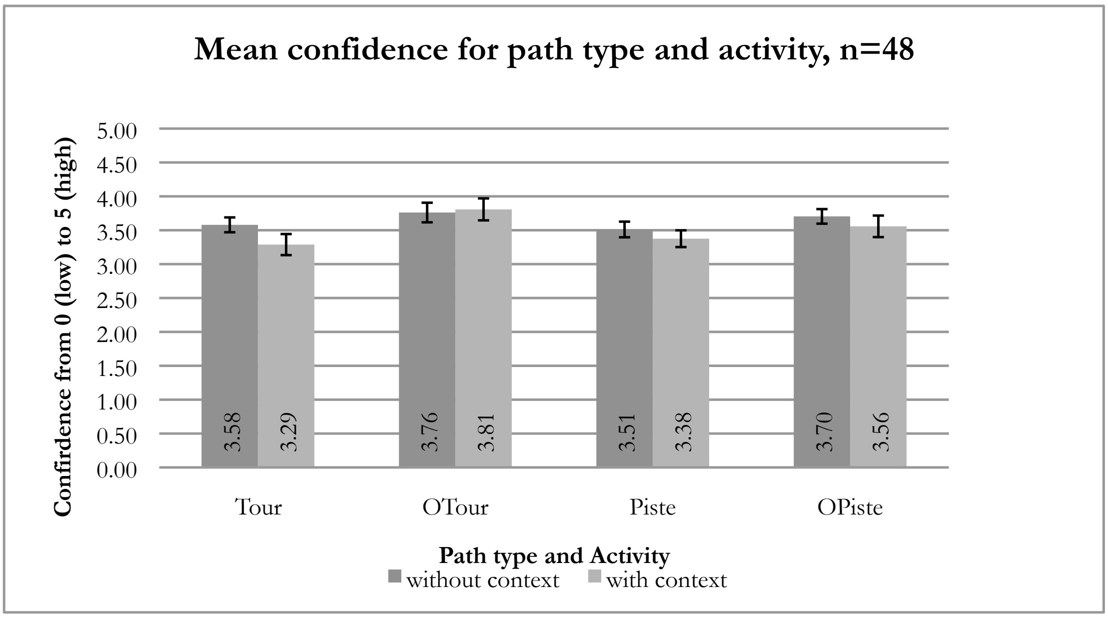


Figure 62: Mean confidence for path type and activity for Experiment III

The result shows an opposite trend though when examining participants' confidence depending on the correctness of the geographic context. When presented with ski touring stimuli confidence decreases with context information, while confidence increases with context information when stimuli from skiing on slopes are shown. Confidence decreases also when presented with a false tour as compared to a correctly located tour. Interestingly though, negative piste stimuli increase participants' confidence as opposed to a positive piste stimulus. In spite of this, when looking at these results graphically, we have to keep in mind that the differences are rather small when it comes to the actual numbers, as Table 16 confirms.

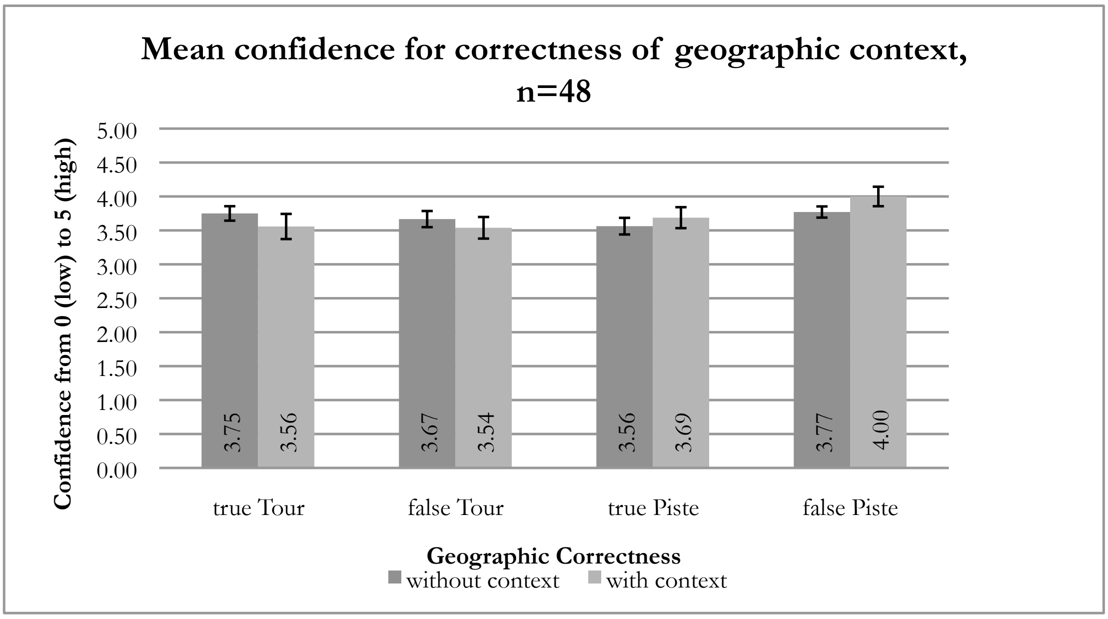


Figure 63: Mean confidence for correct geographic context

The data distribution for confidence, D(48)=.001,p<.05 is also significantly non-normal. The Mann-Whitney test reveals that the distribution of the confidence mean is the same across categories of context. Confidence ratings from participants without context information (mean rank=26.64) did not significantly differ from participants with context information (mean rank=22.69), U=239.00, z=-.975, p<.05(.330).

5.3.6 Results Spatial analysis

The drawn points are also analyzed spatially with ArcMap by organizing the location of the segmentation points into clusters. Clusters are defined when more than one segmentation point has been drawn at the same location. The spatial analysis presents evidence that less segmentation points and clusters have been made for the activity skiing on slopes (M=28 clusters per trajectory) than for the activity ski touring (M=36 clusters). Consequently, the results of the spatial analysis are reported by behavioral context condition, i.e. first the results for the activity tour, followed by the results for the activity piste skiing. For each stimulus we examine the results according to the influence of context, the path type, and the correct geographic context.

For the activity ski touring we can state that in general slightly fewer clusters were generated when participants were presented with the stimuli with geographic context information (see Figure 64). For the closed tour trajectories we have a mean of 68 clusters without context information, and 49 clusters with context information. The open paths have fewer clusters in both conditions, but follow the trend that less clusters appeared with context information (M=28) than without context information (M=36).

Spatially however, the clusters are at the same locations in both conditions as Figure 65 and Figure 66 present (see page 100).

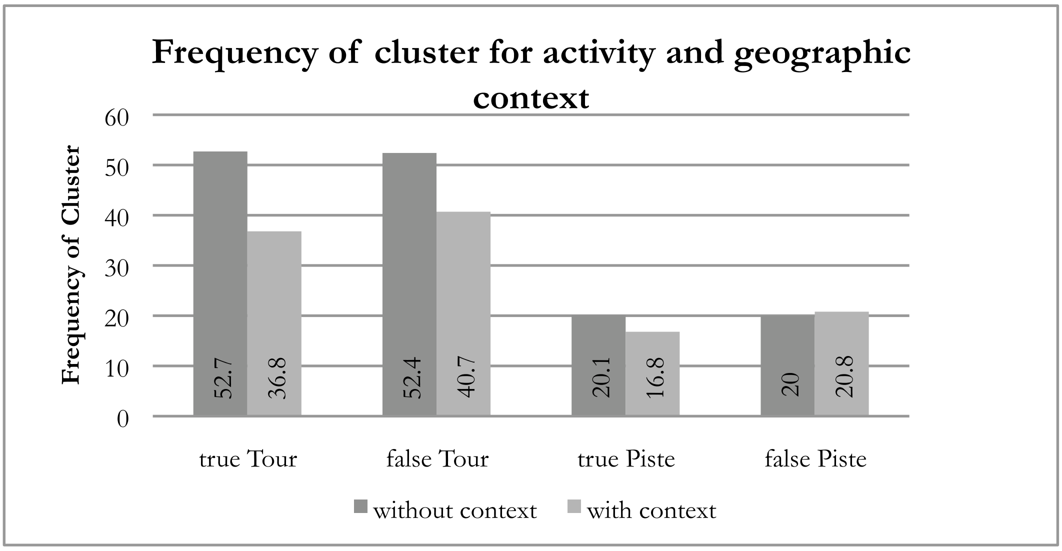


Figure 64: Mean number of cluster according to activity and geographic context

The spatial analysis of the ski touring stimuli show that only three to four clusters for each trajectory are chosen by all participants. All clusters are highlighted in yellow and the top three to four clusters are marked with black surroundings. For these examples of tour stimuli the clusters chosen by all participants are at the beginning and the end of a trajectory. Also the mountain peak is chosen, probably for the fact that the change of direction is very high at this point, as participants without context information also chose this spot. In general we can state that the clusters are mostly at points where the trajectory has a change of direction. This is also true for the other tour stimuli, where the main clusters were generated at the beginning and the end of each trajectory.

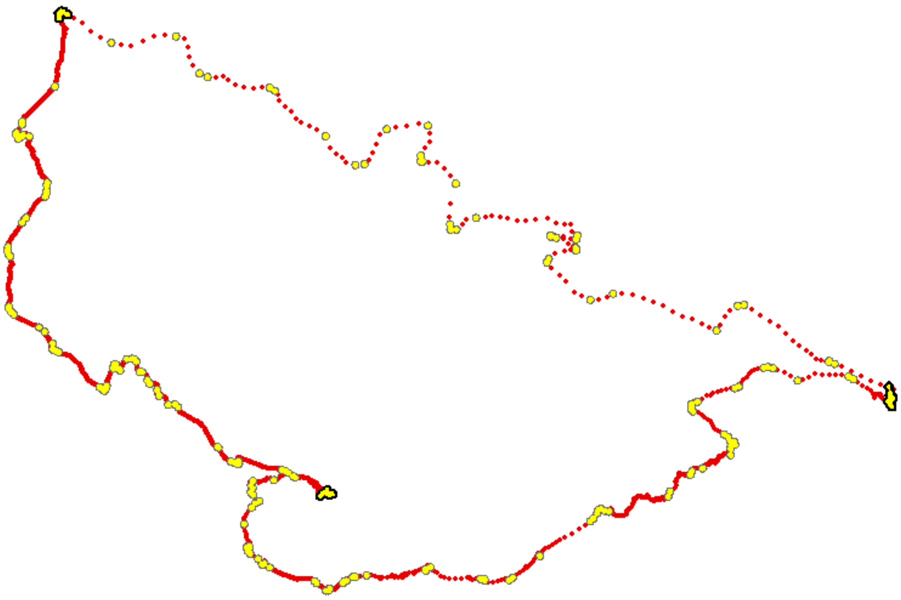


Figure 65: Generated clusters by participants for activity ski touring without context information

Figure 66: Generated clusters by participants for activity ski touring with context information

Similarly, even when comparing the correctness of geographic context, we can hardly see any differences between the two conditions. Following the general trend that the clusters appear at the same locations, we can only see that fewer clusters appear when context information is available. There is an equal number of clusters between correctly located trajectories (M=52 cluster) and incorrectly located trajectories (M=52 clusters), thus no difference is existent. We use one of the ski tour stimuli to show the similarities and differences in Figure 66 and Figure 67. Again, most participants chose the same segmentation points, namely where a change of direction has happened, and thus similar clusters in both conditions appear. We can conclude from these results that the distribution of clusters is independent of context, behavioral context, path type, and the correctness of the geographic context.

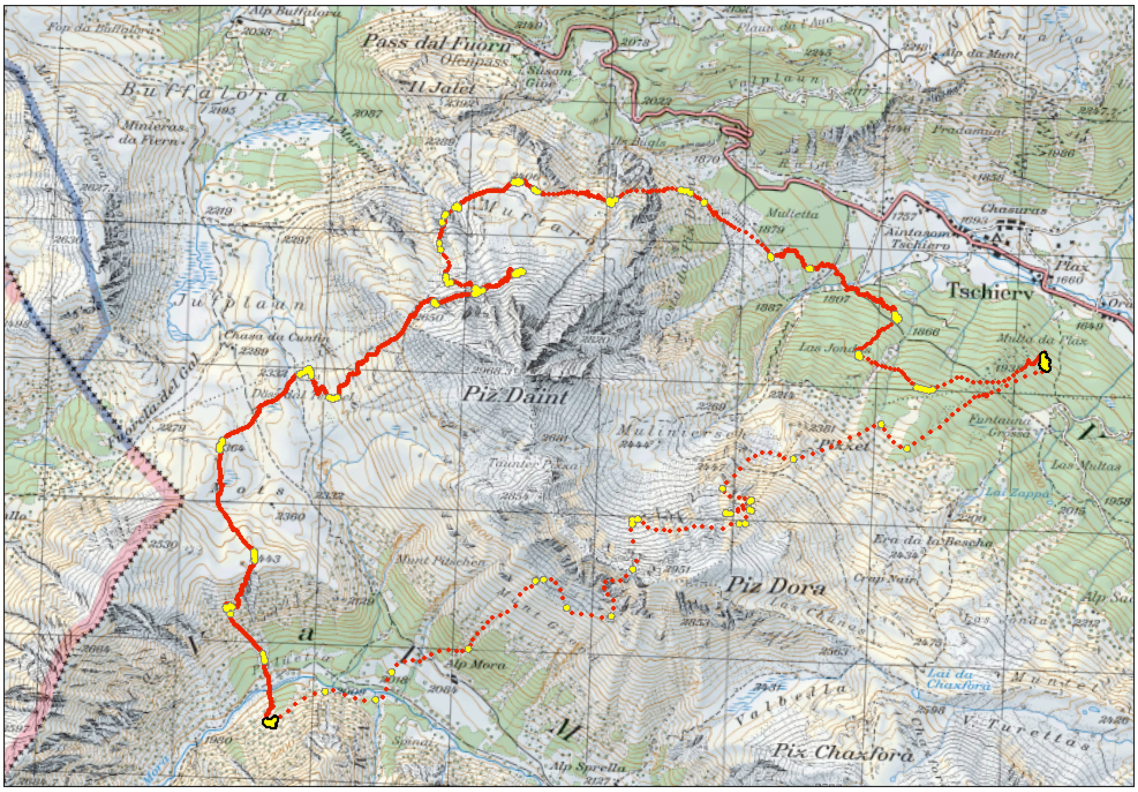


Figure 67: Generated clusters by participants for a false tour trajectory

For the activity skiing on slopes, basically no difference can be identified for the two context conditions. Fewer clusters appear for closed stimuli with context information (M=16) than without context information (M=21), and more clusters appear for open stimuli with context information (M=20) than without context information (M=18) as shown in Figure 68.

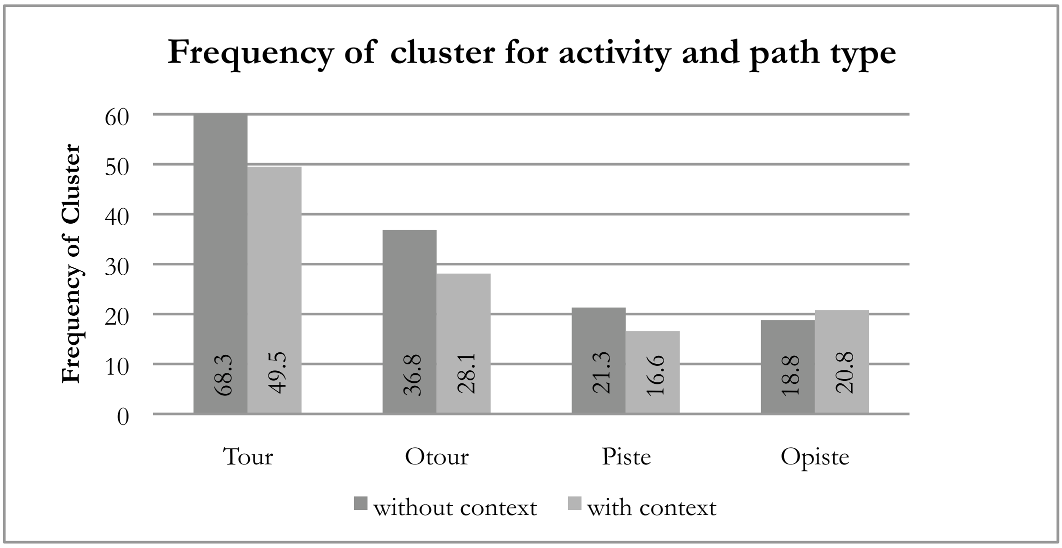


Figure 68: Frequency of cluster for activity and path type

Again we can see similarities for the location of clusters, as Figure 69 and Figure 70 show. Independent of context information the clusters are located at the same spots. Four clusters emerge where all participants have placed circles. These clusters are situated mainly at the beginning and end of the ski lift, thus at the end of the straight lines. Again, the same clusters show up, independent of the context condition.

The results of the spatial analysis relate well to the result of the statistical analysis that context does not matter for the segmentation of the trajectories. Figure 69 shows, as an example, the clusters made for the Piste1 stimulus. This stimulus serves as a prototype for the piste trajectory as the clusters are almost identical in all stimuli for this activity due to the particular shape of the trajectory with its bent and straight lines. The four clusters made by all participants are highlighted in black in Figure 69 and Figure 70.

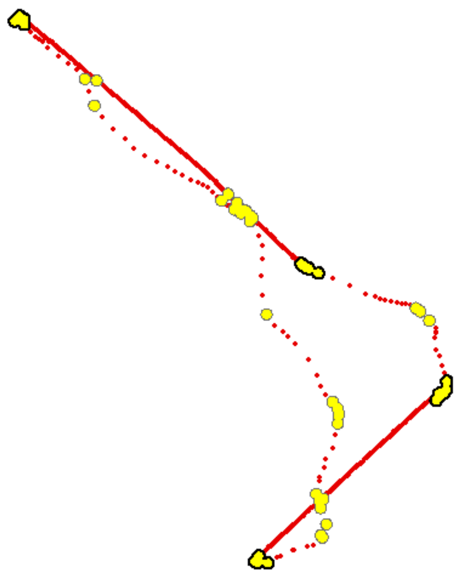


Figure 69: Generated clusters by participants for activity skiing on slopes without context information

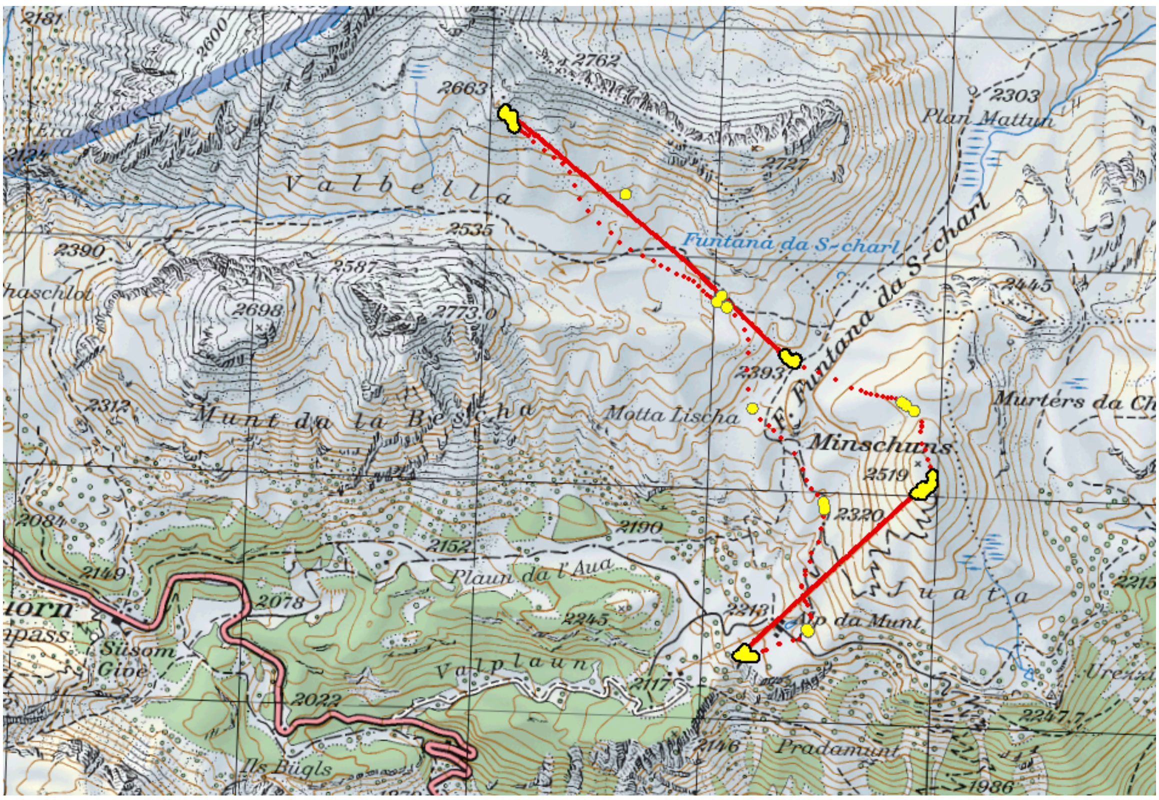


Figure 70: Generated clusters by participants for activity skiing on slopes with context information

When examining the influence of the correctness of the geographic context, we can see that no influence is visually identifiable as the clusters emerge at the same locations, as

Figure 69 and Figure 70 show. Again, the top four clusters are situated at the beginning and end of the straight lines and were identified by all participants. The average number of clusters is also relatively stable as Figure 64 illustrates. We can only see a decrease of clusters when the trajectory is placed in its correct geographic location, and the participants are provided with context information.

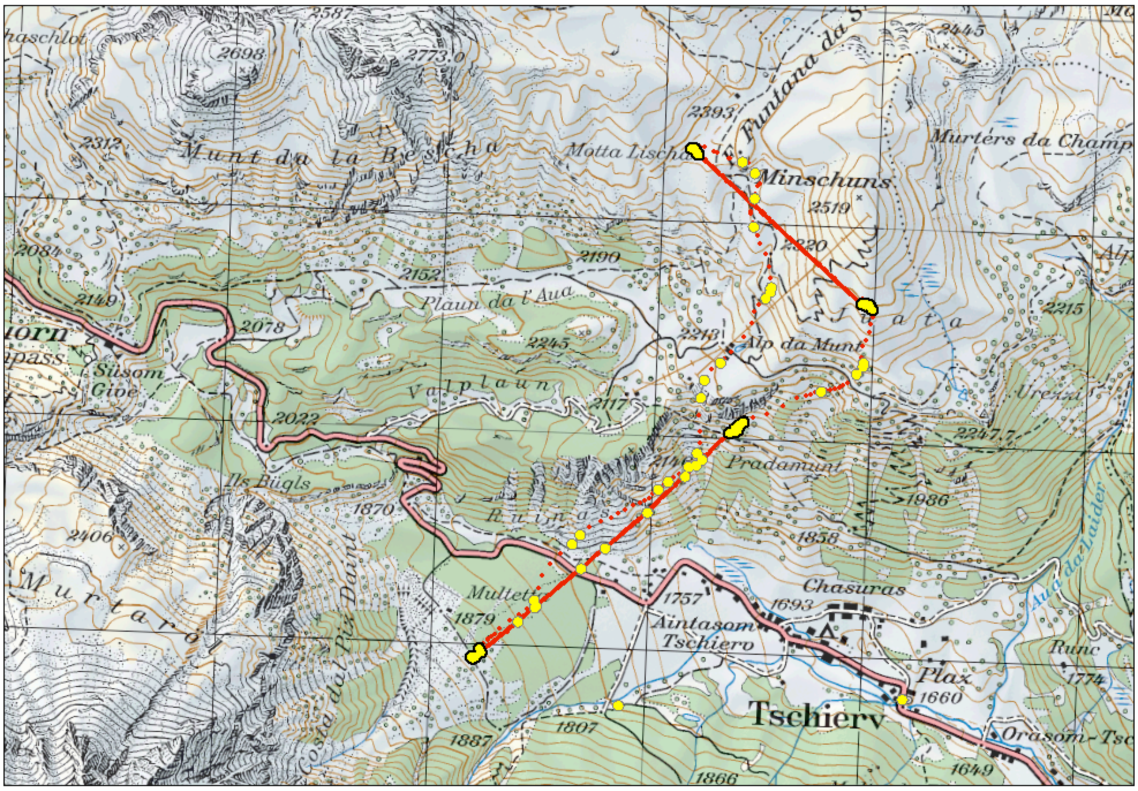


Figure 71: Generated clusters by participants for a false piste trajectory with context information

The results of the spatial analysis lead to the assumption that basic movement parameters, such as change of direction, or speed, are key factors for segmenting the movement trajectories. The majority of the clusters were placed independent of the context condition and independent of the correct or incorrect location of the trajectories at the same spots on the trajectory. Analyzing the categories of the clusters, our assumption gets confirmed. Most clusters are characterized by changes of direction and changes of speed of the moving object, as Figure 72 shows. Change of activity was coded for both conditions, as the shape of the trajectory indicates a larger change in activity, such as the straight and bent lines in the skiing on slopes condition. However, the parameters camp symbols and change of altitude are inherently context dependent, as they are only presented in the context condition. Both parameters failed to have attracted the participants to segment the trajectory at these locations. The cluster categories therefore also present evidence that context does not matter for the segmentation of movement trajectories.

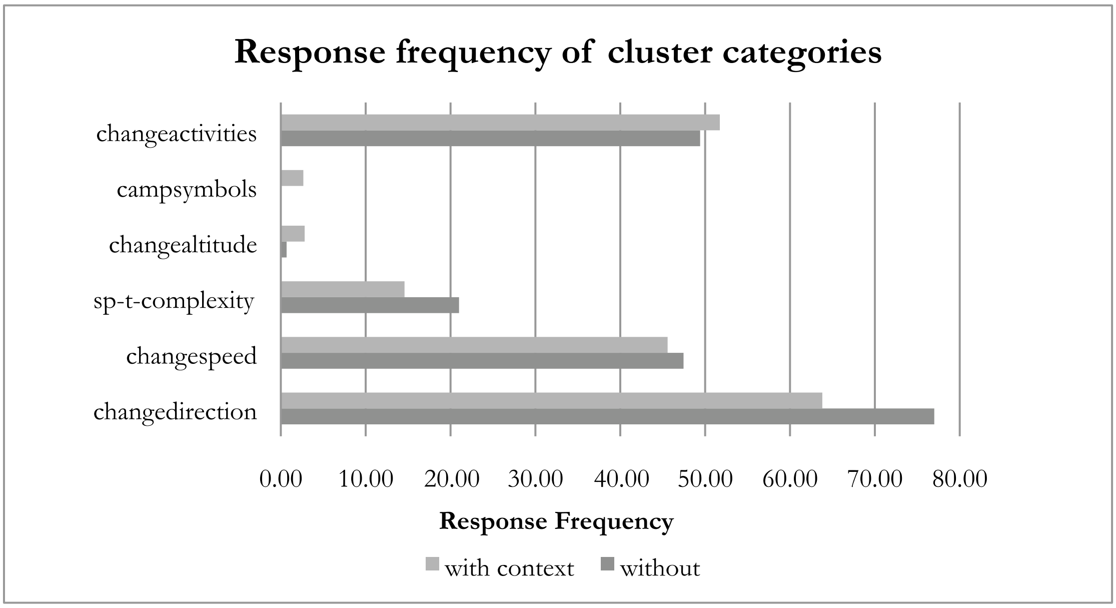


Figure 72: Categories of clusters evaluated according to movement parameters

5.3.7 Summary of Results for Experiment III

The results of the statistical and the spatial analyses show that context does not influence participants' segmentation of movement trajectories. Participants do not make fewer segmentation points when context information is available or choose different segmentation locations, compared to the condition without any context. This result suggests that participants select one segmentation method, and use it consistently throughout the experiment. An example would be a participant who has chosen to segment the trajectory according to changes of directions. Since participants have only been exposed to one context condition, I interpret that the segmentation of trajectories follows an intuitive reasoning, such as the segmentation according to change of direction. The analysis of confidence confirms this result, as the difference between the two conditions is minimal. A reason why confidence does not matter might be explained through the task itself. Participants employ a reasoning strategy for the segmentation that seems reasonable to them, and therefore feel confident, as participants indicated during the experiment. Most clusters are based on geometric movement parameters, which suggest that the segmentation is based on the path geometry. This result is supported by studies from cognitive science (Shipley and Maguire 2008), who found that the segmentation is based on the path geometry in a segmentation experiment. However, the locations where points were drawn show very similar clusters in both conditions. Statistical and spatial analysis have not revealed any effect of the path type in this experiment, as opposed to an earlier assumption by Shipley (2008) that the geometric shape of the path is cognitively and perceptually different.

Behavioral context does have an influence on the number of segmentation points. In general, more segmentation points were made for the activity ski touring than skiing on slopes, but this effect is possibly due to the fact that the ski touring trajectories are longer. Also, the straight lines in the ski piste data naturally inflict the segmentation at the transition from straight to bent lines. Since all piste stimuli had 2-3 straight lines, this naturally means an average of 6-8 points. Confidence values were the same for both behavioral context conditions, and therefore no direct effect can be observed.

The true location of the trajectories within the geographic context does not influence the segmentation. The results of the confidence analysis confirm that the true location of the movement trajectory does not have any significant effect, as participants are equally confident in both conditions. As the spatial distribution of the clusters is very similar in both conditions, we believe participants used the same segmentation method for all tracks without specifically considering context.

I can conclude the summary by answering the two research questions in the following way:

> **Q3a:** Are participants segmenting the movement trajectory according to the basic movement parameters when no geographic context is provided?

Yes, participants mostly use change of direction and change of speed to segment the movement trajectory. However, this is independent of the context condition, but also refers to the participants with context information.

> **Q3b:** Are participants segmenting the trajectory more coarse-grained, based on activity changes, when geographic context information is provided?

No, participants are not using the activity changes as the major segmentation method when context is provided. Also participants with context information segmented the trajectory mainly according to basic movement parameters, as our analysis of the spatial clusters has shown.

5.4 Key Findings from the Experiments

This chapter has examined three human subject experiments, including their methodology and results. The main motivation for doing these experiments was to understand the effect of contextual information on the exploration and analysis of movement data. All three experiments have focused on identifying if context information is relevant for the identification of a moving object and its behavior, as well as the identification of basic movement parameters.

The results of the experiments can be split into three key findings. First, contextual information, in the form of relevant information as well as geographic context, seems to help participants to identify a moving object and its behavior more accurately and more confidently. Second, context information is not necessary for participants to identify basic movement parameters, such as speed, distance, and direction. Also, the segmentation of movement trajectories is done independently of context information and participants have based their segmentation on basic movement parameters, such as change of speed, or change of direction. Third, the incorrect location of the movement trajectory seems to suggest other potential moving objects and their behaviors, i.e. the geographic context influences participants' response accuracy and confidence.

A potential explanation for these contradictory results is potentially that the analysis task determines if context information is necessary for the analysis or not. Context seems not to be required to identify geometric, generic movement parameters of locomotion, i.e. generic movement patterns. However, the analysis of goal-directed movement, i.e. behavioral movement patterns benefits from context information. The big difference between generic patterns and behavioral patterns is therefore the question "why" to understand the process of the underlying behavior rather than understanding the geometric characteristics of the trajectory, thus explaining goal-directed movement rather than locomotion.

By reporting the main findings from the experiments, I have now set the stage for a more in-depth discussion.

6. Discussion

Trying to get an understanding how humans comprehend spatio-temporal data and their visualizations is a key challenge to improve visual analytics tools. I will now revisit the framework and will discuss the relevance of the empirical findings for each individual perspective of the framework.

6.1 Data Perspective

The experiment findings suggest that the analysis task influences the necessity of context information, and particularly the identification of behavioral movement patterns benefits from the integration of context. The empirical results of this research suggest that the separation into generic and behavioral patterns in the taxonomy of movement patterns (Dodge *et al.* 2008) is sensible, since humans also seem to differentiate between two kinds of analyses, namely an analysis of movement parameters (i.e., geometric low-level analysis), or the understanding of the meaning of the movement parameters (i.e., semantic analysis) to identify objects and their behaviors. The shown movement pattern is in both instances the same, but the analyses have two different goals, which is reflected in the separation of two kinds of patterns (i.e., generic and behavioral) in the taxonomy of movement patterns. Since the behavioral patterns are basically generic movement patterns plus the inference of meaning, the term semantic patterns would be more suitable (as described in Section 3.1).

The experiment findings suggest that humans segment trajectories according to similar principles as computational geometry algorithms do. This in turn would mean that work from geographic knowledge discovery (Laube *et al.* 2005; Laube and Purves 2006) and data mining (Benkert *et al.* 2006; Buchin *et al.* 2009; Gudmundsson *et al.* 2004) is valuable for the detection of basic movement parameters, describing locomotion and their generic movement patterns. Movement data algorithms that analyze the geometric properties of movement trajectories can therefore be considered sufficient and indeed seem to support human analysis and understanding of movement data.

Although the formalization of generic movement patterns works without context information, we can understand the semantics of the movement, and therefore the actual movement process, only with context information. Our findings from the first two experiments suggest that movement parameters alone cannot describe a behavioral movement pattern, i.e. adding meaning to the geometric description of the trajectories.

Similarly to Klippel et al. (2009; 2010), our empirical results suggest that the understanding of goal-directed movement can only be achieved by adding context information, and thus the algorithms might not be sufficient yet. This result also means that geographic information of a moving object should not just be integrated as mere attribute information, but also has to be explored as the inherent motivation of an object to move in a certain way. Hence, semantic trajectory modeling (Yan *et al.* 2008) might be a good starting point, because geographic context is explicitly integrated through an ontological module. In this way, importance is not only given to the data collection details, but also the objects domain.

The data analysis process could potentially consist of two complementary steps. A geometric analysis supported by algorithms allows the efficient characterization and geometric description of trajectories, while a semantic analysis with context information allows the user a process analysis to understand movement behavior.

Humans use movement parameters to identify meaningful change points of movement that are represented in the trajectory of movement, for instance change in direction. Since humans understand spatio-temporal processes and movement by structuring the experience into events (Schwan and Garsoffky 2008; Shipley and Zacks 2008; Zacks and Tversky 2001), the results from the segmentation experiment suggest that the events of a movement trajectory are reflected by the basic movement parameters. From a data perspective, Worboys and Hornsby (2004) have already shown that a geospatial event model allows a more powerful modeling approach to dynamic geospatial phenomena. Knowing that event points can be easily identified computationally allows an easier identification and representation of event points in a large data set. Consequently, our empirical findings support the integration of event points as a very promising approach for the exploration, analysis, and representation of generic movement patterns.

6.2 Cognitive Perspective

Literature from cognitive science provides first evidence that humans segment movement processes into events (Kurby and Zacks 2008; Schwan and Garsoffky 2008; Tversky *et al.* 2008). In the last experiment, we also find that participants have used change points, i.e. basic movement parameters, to segment the trajectory independently of context information, and have mainly used ‘change of speed’ and ‘change of direction’ to segment the trajectories. These results are consistent with the postulations that change of location (Schwan and Garsoffky 2008), and movement changes, such as speed

(Tversky *et al.* 2008) influence the segmentation of events. This result makes sense also in the light of our conceptual understanding of motion. Time is perceived through change (Evans and Green 2006) and therefore the most important information lies at the change points of a trajectory. As the change point is conceptually grounded in the source-path-goal schema, it may be particularly useful to highlight change for the effective and efficient data analysis of movement.

Cognitive science uses segmentation with break points to capture events, but therefore the most interesting information lies at the borders of an event (Schwan and Garsoffky 2008; Shipley 2008). By choosing circles in our experiments to segment the trajectories, we are able to actually capture the moment of change, where something important has happened, rather than splitting the moment up. Originally, using circles gave the possibility to capture break points; especially if participants chose the same location, but the center of the circle (and thus the coordinates saved in the data file) did not have the exact same coordinates (as described in Section 5.4.4). In this case the event itself is captured and we could identify 'change of direction' and 'change of speed' as the most common reasons of participants for the segmentation locations. Consequently, the approach is useful to identify event points, i.e. the points of a trajectory with the highest meaning for participants, which can then be used to be highlighted for data mining and visualization.

Segmentation of movements is also influenced by goal-directedness and familiarity (Schwan and Garsoffky 2008; Zacks 2004). Context information possibly provides a solid ground for familiarity, as the experiments have shown that incorrectly placed trajectories lead to less confidence and accuracy, as the second experiment has shown. Zacks (2004; 2009) proposes that the segmentation of movement depends on the movement parameters for fine-grained segmentations, such as change of direction or change of speed, as well as on conceptual features for coarse-grained segmentation, i.e. inferences about the moving objects' goals. The analysis of confidence in the third experiment confirms this result, as the difference between two context conditions is minimal, possibly because participants' employed their own plausible reasoning for the segmentation, and therefore felt confident. The coarse-grained segmentation of events according to Zacks et al. (2009) is based on conceptual ideas about the moving agent. The first two experiments have shown that adding context increases the conceptual understanding of the moving object and its behavior, while the understanding of movement parameters is based on geometric approaches. Maybe context information is especially relevant for coarse-grained segmentation of movement behavior, but less relevant for fine-grained segmentation, i.e. for the understanding of movement parameters.

Within the cognitive perspective, we have gained insights into which extent context information influences the conceptualization of movement in visualizations, namely that it is useful for the identification of an object and its behavior, but not necessarily as important when identifying movement parameters. The understanding of spatio-temporal processes, particularly movement, might therefore be described as a two-step process. In a first instance, participants might detect the basic movement parameters and get an understanding of the geometry of movement trajectories. In a second step, the geometric parameters can potentially be combined with context information about an object, as well as the users' previous knowledge and analysis goal, to get a deeper understanding of the movement process. This process might be comparable to perception and cognition, in which perception is comparable to the understanding of geometric movement parameters, and cognition provides the understanding of movement behavior.

I have to acknowledge that context as defined for this thesis only captures a narrowly defined set of factors, excluding factors such as previous knowledge, or task that also determine and facilitate human's pattern recognition abilities, as we will discuss in Section 6.5.

6.3 Visualization Perspective

The amount of context information needed in a visualization seems to be dependent on the user's analysis task. To detect and extract basic geometric movement parameters, and thus getting an overview on a generic pattern, context information is not necessary, and thus visualizations can be kept as simple as possible, as the results of the first and third experiment indicate that context information did not improve the response accuracy for movement parameters. To analyze the movement process that generated the trajectory, thus getting an understanding of the moving object and its behavior, seems to require more information in the visual display, as the results of the second experiment have shown. Especially the responses to the open questions in the second experiment have shown that the geographic context enabled participants to consider the moving object and its behavior more specifically, and response accuracy and confidence increased. It therefore seems valuable to include geographic context into visualizations of movement, because it enabled participants to leave the pre-attentive level of seeing a pattern, to actually analyzing the movement process and drawing conclusions about the object and its behavior. However, it is not only the amount of context information that influences the response accuracy, response times and confidence of participants, but also the kind of context information. We have seen in these experiments that the inclusion of geographic context provides an average response accuracy of 57%, while the inclusion of title and legend leads to a response accuracy of 54% for the identification of the moving object. This result potentially indicates that an inclusion of geographic context in a graphic display might be more fruitful than a detailed legend and title. The result could also mean that visualizations that show movement data on a map are possibly more effective than visualizations without a map, such as the space-time cube (Hägerstrand 1970). The re-discovered space-time cube shows movement in space on a two-dimensional plane, which enabled Ren and Kwan (Ren and Kwan 2007) to discover interactions between movement behavior in the real and virtual world. The explicit representation of the location of movement might therefore be the success of the space-time cube in recent approaches (Kraak 2003; Kwan *et al.* 2003; Neutens *et al.* 2008), at least when showing few trajectories. On the other hand, the basic movement parameters, or events from a cognitive perspective, are not visualized explicitly in the space-time cube and might therefore hinder the effective recognition of movement patterns. Knowing from the experimental results that change points in a trajectory reflect events from a cognitive perspective, visualizations could potentially be improved by explicitly modeling these event points.

Using event-based approaches is common in geovisualization, as they actively integrate cognitive principles (Aigner *et al.* 2008; Beard 2006; Beard *et al.* 2007; Kapler and Wright 2005; Yattaw 1999). In Aigners (2008) approach, for instance, users specify an event according to spatial, temporal, or attribute dimensions, in order to be able to detect the event later on. Employing computational algorithms to detect change points and suggest them visually to the user might be a useful enhancement to the tool. The user could then rate suggested events according to their importance with respect to the analysis task at hand.

Event points in a movement trajectory reflect the source-path-goal schema as our conceptual understanding of movement processes. Visually representing this understanding in a suitable metaphor could potentially increase the user experience and lead to a better understanding of spatio-temporal processes and behavior. In a static environment the change points of a movement trajectory could be visualized as time stamps on a journey and could potentially be linked with multiple static frames. It also means though, that movement might best be represented though interactive, dynamic visual displays as they represent the internal structure of our time experience, for instance by representing motion with the metaphor "journey".

Visualizations of movement might benefit from the integration of cognitive principles by including geographic context information, as well as visually highlighting events, for instance through salient colors, to potentially enhance visual analytics tools.

6.4 Scope of the Framework

Already Slocum et al. (2001) have stated that the improvement of visualizations can only be accomplished through theory-building, and empirically validated design principles (Fabrikant and Lobben 2009). Current visual analytics tools are information rich in design, but it remains unclear if they support humans in the exploration of movement patterns, as mentioned earlier (Beard *et al.* 2007; Fabrikant *et al.* 2008a). A framework to improve visualizations of movement is a useful stepping-stone to allow the integration of cognitive principles, thus leading to the design of more effective and efficient visual analytics tools. By understanding how users conceptualize spatio-temporal data in visualizations, we can integrate these findings into a cognitively plausible approach, for instance through the visual highlighting of events, or the specific integration of geographic context.

At this stage, the framework is generic enough to support the integration of cognitive principles for any kind of movement pattern, such as transportation geography, urban planning, or meteorology, since only the inclusion of cognitive principles is proposed but no detailed guidelines for specific data are given. Most work, as mentioned earlier, has been done in the formalization of generic movement patterns. Combining the cognitive approach with, for instance, movement ecology and geographic knowledge discovery could potentially lead to the identification of behavioral movement patterns; a key task animal ecologists are aiming for. Combining this framework with a framework introduced by Nathan et al. (2008) would mean an integration of the environmental factors with an analysts' cognitive abilities. The literature review in Section 2.2.1 indicates that data quantity has been traded for data quality, meaning that we can collect all the geometric information of the movement, but the goal of the movement remains unknown. The results of these experiments suggest that understanding the movement of an object is more difficult without context information, as response accuracy and confidence is lower without context information. Conversely, ecologists are actually more interested in the moving agent and its behavior in the first place and not just in some generic pattern that describes the sequence of movement parameters but the actual behavior.

Identifying the key factors that influence humans' understanding by human subject testing is a valuable approach to identify the key elements that improve visual analytics tools, such as the inclusion of geographic context or event-based approaches. This work therefore opens interdisciplinary research avenues to help solve the big goal of understanding movement processes on Earth.

6.5 Limitations

A major contribution of this research is the investigation how context influences the understanding of movement. However, the definition of context used in these experiments is perhaps rather narrow. Using relevant information was inspired by the context awareness literature from mobile computing, but this definition seems to be less useful for the research goals of this thesis. Geographic context, on the contrary, seems to be more relevant as a definition. Two of the experiments use geographic context information and one could repeat the first experiment using geographic context information rather than relevant context information to investigate whether identifying an object and its behavior would be easier with geographic context information also for these tasks. Then other relevant contexts, as mentioned in Section 6.2, could potentially be examined, such as the spatial and temporal scale of the sampled data, to get a broader understanding how context influences the understanding of movement in visualizations.

The third experiment could have been improved by letting participants indicate why they made this particular segmentation, and by labeling the different segments. This might have provided additional insights into what participants assume the object and the behavior is. In this research, participants' reasoning was inferred from finding commonalities between clusters. The categorization of the clusters suggests that the segmentation happens according to basic movement parameters and therefore a geometric analysis of the path. To address the validity of this assumption one could use geometric algorithms to identify change points. If the captured change points form algorithms correspond to the points from human segmentation, it would be possible to confirm that human and algorithmic conceptualizations of movement data complement each other. This approach would also validate the appropriateness of the algorithms at the same time.

Finally, this work focused on how context influences the analysts' understanding of movement data. We therefore interpreted how the task of the analysis influences the understanding of the data. Perceptual and cognitive skills of the analyst, such as their previous knowledge and training, were not further investigated, but an analysis of these factors would be beneficial to get a broader understanding how humans perceive movement.

7. Conclusion and Future Work

7.1 Summary

It was the aim of this thesis to examine how visualizations of movement trajectories are understood and how the inclusion of context can help to understand movement patterns. First, a taxonomy of movement patterns was developed based on a literature review, which differentiates between generic and behavioral movement patterns (Dodge *et al.* 2008). The differentiation into two pattern categories is grounded on the assumption that generic patterns are applicable to all moving objects regardless of context, while behavioral patterns can only be understood with respect to a specific object and its behavior (Dodge *et al.* 2008). Next, I empirically examined whether additional context information facilitates the identification of behavioral movement patterns, as suggested by the taxonomy of movement patterns. Generic and behavioral patterns initially show the same data, and thus also the same pattern. However, generic movement patterns work on a low-level analysis, i.e. the identification of movement parameters, while a higher-level analysis tries to identify the meaning of the pattern, and thus the behavioral pattern. Context information was manipulated by adding relevant information (i.e., title and legend) or geographic context (i.e., terrain map) to visualizations of individual movement trajectories. The results of the empirical evaluations reveal that context information seems not to be a necessary requirement for the identification of basic movement parameters and generic movement patterns. Conversely, context information is necessary to enhance the exploration of behavioral movement patterns. With these findings in mind, I am now revisiting the hypotheses.

7.2 Revisiting the hypotheses

Throughout the thesis we have tried to test the two following hypotheses, as described in Section 3.2:

> *HS_1: Generic movement patterns can be identified through the identification of basic movement parameters, such as speed, distance, direction, and velocity and need no context information of the moving object to understand what movement pattern is visible.*

I can partly confirm this hypothesis statement from the findings of the first and third experiment, as we have clearly seen that no context information is necessary to identify basic movement parameters. However, we have not tested if participants also understand what pattern is visible and if participants would be able to classify the represented trajectory into a generic movement pattern.

HS2: Users need context information of the moving object to correctly identify behavioral patterns and understand why the movement has happened.

This hypothesis can be confirmed by the experiment results of the first and second experiment, where we observed an enhanced understanding of the moving object and its behavior. The experimental results have therefore also confirmed a conceptual difference of generic and behavioral patterns as described in the taxonomy of movement patterns. The understanding of movement parameters and the identification of agent and behavior, thus ultimately the identification of patterns, is therefore conceptually different for users.

I can conclude that geometric path analyses for pattern extraction is useful to find commonalities among movement parameters, but geometric analyses are not useful to understand the inherent motivation that caused movement.

7.3 Scientific Contributions

This research enriches fundamental geographic information science research on space and time concepts, particularly the conceptualization of movement visualization by studying how humans understand visual displays of movement. The particular scientific contribution of this research is two-fold:

1) The development of the conceptual framework is an interdisciplinary approach to integrate knowledge from geographic information science and cognitive science, as an approach to enhance visual analytics tools for the exploration and identification of movement patterns.
2) The empirical assessment of context information has shown that it is valuable for the user to include context information for the exploration of behavioral movement patterns. Using geometric path analyses are effective to identify key components of the trajectory and to allow the categorization of generic movement patterns.

7.4 Future Work

Section 6.5 has shown limitations of the experiments that deserve attention to improve future work in this research area.

7.4.1 Taxonomy and Framework

Combining the data, cognitive, and visualization perspective is a good starting point to improve visual analytics tools in a cognitively inspiring way. Integrating it into key research areas, such as movement ecology, transportation geography, meteorology, hazard evacuation planning, etc., is largely missing, but might potentially result in a more general applicability of tools not just for specific research groups.

Working together with an application domain, for instance movement ecology, would have also overcome some general limitations of the taxonomy of movement patterns, mainly its incompleteness regarding the behavioral patterns. At this stage, no classification exists for the behavioral patterns, but they could be organized by pattern structure depending on the involved movement parameters, similar to the generic patterns, or according to the moving agent, such as animals, or humans. Identifying all meaningful behavioral patterns would be an important step forward and opens cross-disciplinary research avenues to understand movement behavior.

The results have also shown that the cognition function (as described in Chapter 3.1) to improve visualizations of movement could not yet be solved. Future work is needed to coherently identify all cognitive factors influencing the user. This thesis has only studied the influence of context on the users' understanding of movement, but cognition and perception of a user are far more complex than this simplified model. Identifying user needs would contribute to establishing a consistent framework for movement visualizations in order to improve the design of visual analytics tools.

7.4.2 Improvements for Empirical Testing

I have tested in this thesis how context, as a facilitator for previous knowledge influences humans' understanding of visualizations of movement. While we clearly state that context information helps users exploring behavioral patterns, we do not think that context is the only factor influencing the understanding of movement data. Other cognitive factors, like familiarity and training with handling movement data, and the respective representations, have not been investigated. Visual analytics would also benefit from understanding which analyses tasks influence the user in what way to help users perform their analyses, such as a narrow identification task, e.g. detection of speed changes, as opposed to much broader data exploration tasks.

The definition of context used in these experiments is fairly narrow and focuses on relevant information and geographic reference of the moving object. It would be necessary in future work to assess other context definitions, especially the spatial and temporal scale of moving objects.

In our experiments we have tested the identification of moving objects as well as the identification of movement parameters. However, we have not tested if actual patterns are recognizable by participants. We could imagine a scenario where users have to sort visual representations of patterns to get an understanding which key factors are important for a respective classification. One classification could be the number of direction changes or changes of speed, another specific geographic terrains of moving objects. All these classification schemes would ideally lead to a suitable classification of movement patterns and could potentially enhance the taxonomy of movement patterns.

One of the original key challenges though is the representation of large amounts of movement data. So far all visualizations in the experiments show one movement trajectory from one object, but most visualizations fail when the representation gets overloaded and crowded. As a next step it would be necessary to test displays with multiple trajectories, to identify when visualizations break down and why.

7.4.2 Design Guidelines for Visualizations

Working on empirically validated design guidelines for movement visualizations also remains an open research avenue, as the project has not dealt with the actual integration of the findings into visualizations. A major research avenue is therefore the implementation of cognitively inspired visualizations. A way to integrate the experiment findings would be to detect events through algorithms and then make events visually salient for users, for example by applying appropriate visual variables, e.g. color hue or motion. This approach would highlight the important information and could potentially augment people's capabilities for pattern extraction and complex spatio-temporal reasoning.

References

Aigner, W., Miksch, S., Müller, W., Schumann, H. and Tominski, C. (2008). Visual Methods for Analyzing Time-Oriented Data. *Transactions on Visualization and Computer Graphics* Vol. 14(1): 47-60.

Andersson, M., Laube, P., Wolle, T. and Gudmundsson, J. (2008). Reporting leaders and followers among trajectories of moving point objects. *GeoInformatica* Vol. 12(4): 497-528.

Andrienko, G., Andrienko, N., Demsar, U., Dransch, D., Dykes, J., Fabrikant, S.I., Jern, M., Kraak, M.-J., Schumann, H. and Tominski, C. (2010). Space, Time, and Visual Analytics. *International Journal of Geographic Information Science* Vol. 24(10): 1577-1600.

Andrienko, G., Andrienko, N., Dykes, J., Fabrikant, S.I. and Wachowicz, M. (2008a). Geovisualization of Dynamics, Movement and Change: key issues, and developing approaches in visualization research. *Special Issue on Geovisualization of Dynamics, Movement and Change. Information Visualisation* Vol. 7(3): 173-180.

Andrienko, G., Andrienko, N., Dykes, J., Fabrikant, S.I. and Wachowicz, M. (2008b). Geovisualization of Dynamics, Movement and Change: key issues, and developing approaches in visualization research. *Information Visualization* Vol. Special Issue on Geovisualization of Dynamics, Movement and Change Vol.7(3): 173-180.

Andrienko, G., Andrienko, N. and Wrobel, S. (2007). Visual Analytics Tools for Analysis of Movement Data. *ACM SIGKDD Explorations* Vol. 9(2): 38-46.

Andrienko, N., Andrienko, G. and Gatalsky, P. (2003). Exploratory spatio-temporal visualization: an analytical review. *Journal of Visual Languages and Computing* Vol. 14(6): 503-541.

Axhausen, K.W. and Gärling, T. (1992). Activity-based approaches to travel analysis: conceptual frameworks, models, and research problems. *Transport Reviews* Vol. 12(4): 323-341.

Beard, K. (2006). Modelling Change in Space and Time: An Event-Based Approach. *Dynamic and Mobile GIS: Investigating Change in Space and Time*. Drummond, J., Billen, R., Forrest, D. and Joao, E., Eds. Boca Raton, FL, Taylor and Francis**:** 55-77.

Beard, K., Deese, H. and Pettigrew, N.R. (2007). A framework fo visualization and exploration of events. *Information Visualization* Vol. 7: 133-151.

Benkert, M., Gudmundsson, J., Huebner, F. and Wolle, T. (2006). *Reporting Flock Patterns*. ESA, Springer, Berlin: 660-671.

Bertin, J. (1983). *Semiology of Graphics: Diagrams, Networks, Maps*. Madison, University of Wisconsin Press.

Blok, C. (2000). Monitoring Change: Characteristics of Geospatial Phenomena for Visual Exploration. *Lecture Notes In Computer Science; Spatial Cognition II, Integrating Abstract Theories, Empirical Studies, Formal Methods, and Practical Applications* London, UK, Springer. 1849**:** 16-30.

Bogacz, S. and Trafton, J.G. (2005). Understanding dynamic and static displays: using images to reason dynamically. *Cognitive Systems Research* Vol. 6(4): 312-319.

Boroditsky, L. (2000). Metaphoric structuring: understanding time through spatial metaphors. *Cognition* Vol. 75: 1-28.

Buchin, K., Buchin, M., van Kreveld, M. and Luo, J. (2009). Finding Long and Similar Parts of Trajectories. *ACM GIS*. Seattle, Washington, USA.

Casasanto, D. and Boroditsky, L. (2008). Time in the mind: Using space to think about time. *Cognition* Vol. 106: 579-593.

Casati, R. and Varzi, A.C. (2008). Event Concepts. *Understanding Events*. Shipley, T.F. and Zacks, J.M., Eds. Oxford, Oxford University Press: 31-53.

Chellappa, R., Cuntoor, N.P., Joo, S.-W., Subrahmanian, V.S. and Turaga, P. (2008). Computational Vision Approaches for Event Modeling. *Understanding Events - From Perception to Action*. Shipley, T.F. and Zacks, J.M., Eds. Oxford, Oxford University Press: 473-521.

Chen, C. (2005). Top 10 unsolved information visualization problems. *IEEE Computer Graphics and Applications* Vol. 25(4): 12-16.

Chen, J., MacEachren, A. and Guo, D. (2008). Supporting the Process of Exploring and Interpreting Space-Time Multivariate Patterns: The Visual Inquiry Toolkit. *Cartography and Geographic Information Science* Vol. 35(1): 33-50.

Cöltekin, A., Fabrikant, S.I. and Lacayo, M. (2010). Exploring the efficiency of users' visual analytics strategies based on sequence analysis of eye movement recordings. *International Journal of Geographic Information Science* Vol. 24(10): 1559-1575.

Cöltekin, A., Heil, B., Garlandini, S. and Fabrikant, S.I. (2009). Evaluating the Effectivness of Interactive Map Interface Designs: A Case Study Integrating Usability Metrics with Eye Movement Analysis. *Cartography and Geographic Information Science* Vol. 36(1): 5-17.

Demsar, U. (2007). Combining Formal and Exploratory Methods for Evaluation of an Exploratory Geovisualization Application in a Low-Cost Usability Experiment. *Cartography and Geographic Information Science* Vol. 34(1): 29-45.

Dey, A.K. and Abowd, G.D. (2000). Towards a better understanding of context and context-awareness. *Workshop on the What, Who, Where, When and How of Context-Awareness at CHI*: 2000.

DiBiase, D.W., MacEachren, A., Krygier, J.B. and Reeves, C. (1992). Animation and the Role of Map Design in Scientific Visualization. *Cartography and Geographic Information Systems* Vol. 19(4): 201-214.

Dodge, S., Weibel, R. and Forootan, E. (2009). Revealing the physics of movement: Comparing the similarity of movement characteristics of different types of moving objects. *Computers, Environment and Urban Systems* Vol. 33: 419-434.

Dodge, S., Weibel, R. and Lautenschütz, A.-K. (2008). Towards a Taxonomy of Movement Patterns. *Information Visualization* Vol. 7: 240-252.

Doherty, S.T., Miller, E.J., Axhausen, K.W. and Gärling, T. (2002). A conceptual model of the weekly household activity-travel scheduling process. *Travel Behavior: Spatial Patterns, Congestion and Modelling*. Stern, E., Salamon, I. and Bovy, P.H.L., Eds. Cheltenham, Edward Elgar: 233-264.

Dykes, J. and Mountain, D.M. (2003). Seeking structure in records of spatio-temporal behaviour: visualization issues, efforts and applications. *Computational Statistics & Data Analysis* Vol. 43: 581-603.

Evans, V. and Green, M. (2006). *Cognitive Linguistics - An Introduction*. Edinburgh, UK, Edinburgh University Press.

Fabrikant, S.I. and Lobben, A. (2009). Introduction: Cognitive Issues in Geographic Information Visualization. *Cartographica* Vol. 44(3): 139-143.

Fabrikant, S.I., Rebich-Hespanha, Andrienko, N., Andrienko, G. and Montello, D.R. (2008a). Novem Method to Measure Inference Affordance in Static Small-Multiple Map Displays Representing Dynamic Processes. *The Cartographic Journal* Vol. 45(3): 201-215.

Fabrikant, S.I., Rebich-Hespanha, S., Andrienko, N., Andrienko, G. and Montello, D.R. (2008b). Novel Method to Measure Inference Affordance in Static Small Multiple Displays Representing Dynamic Processes. *The Cartographic Journal* Vol. 45(3): 201-215.

Fabrikant, S.I., Rebich-Hespanha, S. and Hegarty, M. (2010). Cognitively Inspired and Perceptually Salient Graphic Displays for Efficient Spatial Inference Making. *Annals of the Association of American Geographers* Vol. 100(1): 1-17.

Fabrikant, S.I. and Skupin, A. (2005). Cognitively Plausible Information Visualization. *Exploring Geovisualization*. Dykes, J., MacEachren, A. and Kraak, M.-J., Eds. Amsterdam, The Netherlands, Elsevier: 667-690.

Forer, P. and Huisman, O. (2001). *Dynamic geographies and space-time acitivity patterns*. 22nd New Zealand Geographical Society Conference, Otago, New Zealand.

Frair, J.L., Fieberg, J., Hebblewhite, M., Cagnacci, F., DeCesare, N.J. and Pedrotti, L. (2010). Resolving issues of imprecise and habitat-biased locations in ecological analyses using GPS telemetry data. *Philosophical Transactions of The Royal Society Biological Sciences* Vol. 365: 2187-2200.

Fuhrmann, S., Ahonen-Rainio, P., Edsall, R.M., Fabrikant, S.I., Koua, E.L., Tobón, C., Ware, C. and Wilson, S. (2005). Making useful and usable geovisualization: design and evaluation issues. *Exploring Geovisualization*. Dykes, J., MacEachren, A. and Kraak, M.-J., Eds. Amsterdam, The Netherlands, Elsevier: 553-566.

Gahegan, M. (2001). Visual exploration in geography: analysis with light. *Geographic Data Mining and Knowledge Discovery*. Miller, H.J. and Han, J., Eds. London, Taylor & Francis: 260-287.

Garlandini, S. (2009). Perceptual Salience and Thematic Relevance in 2D Map Displays. *Department of Geography*. Zürich, University of Zürich. Master.

Garlandini, S. and Fabrikant, S.I. (2009). *Evaluating the Effectiveness and Efficiency of Visual Variables for Geographic Information Visualization*. Spatial Information Theory COSIT Aber Wrac'h, France, September 21-25, 2009, Springer 195-211.

Gentner, D., Imai, M. and Boroditsky, L. (2002). As time goes by: Evidence for two systems in processing space-time metaphors. *Language and Cognitive Processes* Vol. 17(5): 537-565.

Goldberg, J.H. and Kotval, X.P. (1999). Computer interface evaluation using eye movements: methods and constructs. *International Journal of Industrial Ergonomics* Vol. 24: 631-645.

Golledge, R.G. and Stimson, R.J. (1997). *Spatial Behavior: A Geographic Perspective*. New York, The Guilford Press.

Grenon, P. and Smith, B. (2004). SNAP and SPAN: Towards Dynamic Spatial Ontology. *Spatial Cognition and Computation* Vol. 1: 69-104.

Gudmundsson, J. and van Kreveld, M. (2006). *Computing Longest Duration Flocks in Trajectories*. ACM GIS.

Gudmundsson, J., van Kreveld, M. and Speckmann, B. (2004). Efficient Detection of Motion Patterns in Spatio-Temporal Data Sets. *ACM GIS*. New York: 250-257.

Hägerstrand, T. (1970). What about people in regional science? *Papers of Regional Science Association* Vol. 24: 7-21.

Haggett, P. (2001). *Geography: A Global Synthesis*. Harlow, U.K., Prentice Hall.

Haklay, M. and Zafiri, A. (2008). Usability Engineering for GIS: Learning from a Screenshot. *The Cartographic Journal* Vol. 45(2): 87-97.

Hao, M.C., Dayal, U., Keim, D.A. and Schreck, T. (2005). *Importance-Driven Visualization Layouts for Large Time Series Data*. IEEE Symposium on Information Visualization (InfoVis 2005), Minneapolis, MN, USA, October 23-25.

Harrower, M. (2007). The Cognitive Limits of Animated Maps. *Cartographica* Vol. 42(4): 349-357.

Hedley, N.R., Drew, C.H. and Lee, A. (1999). Hagestrand Revisited: Interactive Space-Time Visualizations of Complex Spatial Data. *Informatica* Vol. (2): 155- 168.

Hochheiser, H. and Shneiderman, B. (2001). *Visual Specification of Queries for Finding Patterns in Time-Series Data*. Discovery Science Washington, DC: 441-446.

Hornsby, K. and Egenhofer, M.J. (2000). Identity-based change: a foundation for spatio-temporal knowledge representation. *International Journal of Geographical Information Science* Vol. 14(3): 207-224.

Hornsby, K. and Egenhofer, M.J. (2002). Modeling Moving Objects over Multiple Granularities. *Annals of Mathematics and Artificial Intelligence* Vol. 36 Special Issue on Spatial and Temporal Granularity(1-2): 177-194.

Hornsby Stewart, K. and Cole, S. (2007). Modeling moving geospatial objects from an event-based perspective. *Transactions in GIS* Vol. 11(4): 555-573.

Kapler, T. and Wright, W. (2005). GeoTime information visualization. *Information Visualization* Vol. 4(2): 136-146.

Keim, D.A., Mansmann, F., Schneidewind, J. and Ziegler, H. (2006). *Challenges in Visual Data Analysis*. Information Visualization, London, United Kingdom, July 5-7, IEEE Press.

Klippel, A. (2009). Topologically characterized movement patterns: A cognitive assessment. *Spatial Cognition and Computation* Vol. 9(4): 233-261.

Klippel, A. and Li, R. (2009). *The Endpoint Hypothesis: A Topological-Cognitive Assessment of Geographic Scale Movement Patterns*. International Conference on Spatial Information Theory (COSIT), Aber Wrac'h, France, September 21-25, 2009, Springer LNCS: 177-194.

Klippel, A., Li, R., Hardisty, F. and Weaver, C. (2010). *Cognitive Invariants of Geographic Event Conceptualization: What Matters and What Refines?* International Conference on Geographic Information Science, GIScience 2010, Zurich, Switzerland, 14-17.9.2010, Springer: 130-144.

Klippel, A., Worboys, M. and Duckham, M. (2007) Identifying factors of geographic event conceptualisation *International Journal of Geographical Information Science*, 1-22.

Kraak, M.-J. (2003). *The Space-Time Cube revisited from a geovisualization perspective*. 21st International Cartographic Conference, Durban, South Africa: 1988-1996.

Kurby, C.A. and Zacks, J.M. (2008). Segmentation in the perception and memory of events. *Trends in Cognitive Sciences* Vol. 12(2): 72-79.

Kwan, M.-P. (2000). Interactive geovisualization of activity-travel patterns using three-dimensional geographical information systems: a methodological exploration with a large data set. *Transportation Research Part C* Vol. 8: 185-203.

Kwan, M.-P. (2004). GIS Methods in Time-Geographic Research: Geocomputation and Geovisualization of Human Activity Patterns. *Geografiska Annaler B* Vol. 86(4): 267-280.

Kwan, M.-P., Janelle, D.G. and Goodchild, M.F. (2003). Accessibility in space and time: A theme in spatially integrated social science. *Journal of Geographical Systems* Vol. 5: 1-3.

Lakoff, G. (1987). *Women, fire, and dangerous things: What categories reveal about the mind*. Chicago, University of Chicago Press.

Lakoff, G. and Johnson, M. (1980). *Metaphors We Live By*. London, The University of Chicago Press.

Langran, G. (1992). *Time in Geographic Information Systems*. London, Taylor & Francis.

Laube, P., Dennis, T., Forer, P. and Walker, M. (2007a). Movement beyond the snapshot - Dynamic analysis of geospatial lifelines. *Computers, Environment and Urban Systems* Vol. 31(5): 481-501.

Laube, P., Imfeld, S. and Weibel, R. (2005). Discovering relative motion patterns in groups of moving point objects. *International Journal of Geographical Information Science* Vol. 19(6): 639-668.

Laube, P. and Purves, R.S. (2006). An approach to evaluating motion pattern detection techniques in spatio-temporal data. *Computers, Environment and Urban Systems* Vol. 30: 347-374.

Laube, P., Purves, R.S., Imfeld, S. and Weibel, R. (2007b). Analysing Point Motion with Geographic Knowledge Discovery Techniques. *Dynamic and Mobile GIS: Investigating Changes in Space and Time*. Drummond, J., Billen, R., Joao, E. and Forrest, D., Eds. Boca Raton, FL, Taylor and Francis. **:** 263-287.

Lautenschütz, A.-K. (2009). *Evaluating the importance of contextual informatin in visual displays of movement patterns*. COSIT Doctoral Colloquium, Aber Wrac'h, France, September 21-25, 2009.

Lautenschütz, A.-K. (2010). *How context influences the segmentation of movement trajectories - an experimental approach for environmental and behavioral context*. GIScience 2010, Zurich, Switzerland, September 14-18: Extended Abstracts online: http://www.giscience2010.org/index.php?page=content.

Lee, P.U. and Klippel, A. (2005). *Dynamic aspects of spatial information in air traffic controller displays*. AAAI Spring Symposium Series, Reasoning with Mental and External Diagrams: Computational Modeling and Spatial Assistance, Stanford University, California, AAAI Press.

Li, X., Cöltekin, A. and Kraak, M.-J. (2010). *Visual exploration of eye movement data using the Space-Time Cube*. GIScience LNCS Lecture Notes in Computer Science: 295-309.

Lin, J., Keogh, E. and Lonardi, S. (2005). Visualizing and discovering non-trivial patterns in large time-series databases. *Information Visualization* Vol. 4(2): 61-82.

Lu, Q., Chen, F. and Hancock, K. (2009). On path anomaly detection in a large transportation network. *Computers, Environment and Urban Systems* Vol. 33(6): 448-462.

MacEachren, A. and Kraak, M.-J. (2001). Research Challenges in Geovisualization. *Cartography and Geographic Information Science* Vol. 28(1): 3-12.

Martin, D.M. (2008). *Doing Psychology Experiments*. Belmont, CA, Thomson Wadsworth.

Mennis, J. and Guo, D. (2009). Spatial data mining and geographic knowledge discovery - An introduction. *Computers, Environment and Urban Systems* Vol. 33: 403-408.

Mennis, J.L., Peuquet, D.J. and Qian, L. (2000). A conceptual framework for incorporating cognitive principles into geographical database representation. *International Journal of Geographical Information Science* Vol. 14(6): 501-520.

Miller, H.J. (1991). Modelling Accessibility Using Space-Time Prism Concepts within Geographical Information Systems. *International Journal of Geographical Information Systems* Vol. 5(3): 287-301.

Miller, H.J. and Han, J. (2001). Geographic data mining and knowledge discovery: An Overview. *Geographic Data Mining and Knowledge Discovery*. Miller, H.J. and Han, J., Eds. London, Taylor and Francis**:** 3-12.

Moore, A.B., Whigham, P., Holt, A., Aldridge, C. and Hodge, K. (2003). *A Time Geography Approach to the Visualization of Sport*. 7th International Conference on GeoComputation.

Nathan, R., Getz, W.M., Revilla, E., Holyoak, M., Kadmon, R., Saltz, D. and Smouse, P.E. (2008). A movement ecology paradigm for unifying organismal movement research. *Proceedings of the National Academy of Science USA* Vol. 105: 19060-19065.

Neutens, T., Van de Weghe, N., Witlox, F. and De Maeyer, P. (2008). A three-dimensional network-based space0time prism. *Journal of Geographical Systems* Vol. 10: 89-107.

Newtson, D. (1973). Attribution and the unit of perception of ongoing behavior. *Journal of Personality and Social Psychology* Vol. 28: 28-38.

Newtson, D. and Engquist, G. (1976). The perceptual organization of ongoing behavior. *Journal of Experimental Social Psychology* Vol. 12: 436-450.

Norman, D.A. (2002). *The Design of Everyday Things*. New York, USA, Basic Book Publishers.

Paillard, J. (1991). Motor and representational framing of space. *Brain and Space*. Paillard, J., Ed. Oxford, Oxford University Press: 163-182.

Peuquet, D.J. (1994). It's about Time: A Conceptual Framework for the Representation of Temporal Dynamics in Geographic Information Systems. *Annals of the Association of American Geographers* Vol. 84(3): 441-461.

Peuquet, D.J. and Duan, N. (1995). An event-based spatio-temporal data model (ESTDM) for temporal analysis of geographical data. *International Journal of Geographical Information Science* Vol. 9(1): 7-24.

Peuquet, D.J. and Kraak, M.-J. (2002). Geobrowsing: creative thinking and knowledge discovery using geographic visualization. *Information Visualization* Vol. 1: 80-91.

Phan, D., Xiao, L., Yeh, R., Hanrahan, P. and Winograd, T. (2005). Flow map layout. *IEEE Symposium on Information Visualization*: 219-224.

Raper, J. (2000). *Multidimensional Geographic Information Science*. London, Taylor and Francis Group.

Raubal, M., Miller, H.J. and Bridwell, S. (2004). User Centered Time Geography For Location-Based Services. *Geografiska Annaler B* Vol. 86(4): 245-265.

Ren, F. and Kwan, M.-P. (2007). Geovisualization of Human Hybrid Activity-Travel Patterns. *Transactions in GIS* Vol. 11(5): 721-744.

Robinson, A., Chen, J., Lengerich, E.J., Meyer, H.G. and MacEachren, A.M. (2005). *Combining Usability Techniques to Design Geovisualization Tools for Epidemiology*. Auto-Carto, Las Vegas, NV, March 18-23.

Schilit, B., Adams, N. and Want, R. (1994). *Context-Aware Computing Applications*. International Workshop on Mobile Computing Systems and Applications: 85-90.

Schmid, F., Richter, K.-F. and Laube, P. (2009). *Semantic Trajectory Compression*. Advances in Spatial and Temporal Databases - 11th International Symposium, SSTD 2009, Springer: 411-416.

Schmidt, A., Beigl, M. and Gellersen, H.-W. (1999). There is more to context than location. *Computers & Graphics Journal* Vol. 23(6): 893-902.

Schwan, S. and Garsoffky, B. (2008). The Role of Segmentation in Perception and Understanding of Events. *Understanding Events - From Perception to Action*. Shipley, T.F. and Zacks, J.M., Eds. Oxford, Oxford University Press: 391-414.

Schwartz, R. (2008). Events Are What We Make Of Them. *Understanding Events - From Perception to Action*. Shipley, T.F. and Zacks, J.M., Eds. Oxford, Oxford University Press: 54-60.

Shaw, S.-L., Bombom, L.S. and Yu, H. (2008). A Space-Time GIS Approach to Exploring Large Individual-Based Spatiotemporal Datasets. *Transactions in GIS* Vol. 12(4): 425-441.

Shipley, T.F. (2008). An Invitation to an Event. *Understanding Events - From Perception to Action*. Shipley, T.F. and Zacks, J.M., Eds. Oxford, Oxford University Press: 3-30.

Shipley, T.F., Fabrikant, S.I. and Lautenschütz, A.-K. (2010). Creating perceptually salient animated displays of spatially coordinated events. *Las Navas 2010: Cognitive and Linguistic Aspects of Geographic Space*. Las Navas del Marques, Avila, Spain.

Shipley, T.F. and Maguire, M.J. (2008). Geometric Information for Event Segmentation. *Understanding Events - From Perception to Action*. Shipley, T.F. and Zacks, J.M., Eds. Oxford, Oxford University Press: 415-435.

Shipley, T.F. and Zacks, J.M., Eds. (2008). *Understanding Events - From Perception to Action*. Oxford Series in Visual Cognition. Oxford, Oxford University Press.

Shneiderman, B. (1996). *The eyes have it: a task by data type taxonomy for information visualizations*. IEEE Symposium on Visual Languages: 336-343.

Slocum, T.A. (1998). *Thematic Cartography and Visualization*, Prentice Hall.

Slocum, T.A., Blok, C., Jiang, B., Koussoulakou, A., Montello, D.R., Fuhrmann, S. and Hedley, N.R. (2001). Cognitive and Usability Issues in Geovisualization. *Cartography and Geographic Information Science* Vol. 28(1): 61-75.

Smallman, H.S., St.John, M. and Oonk, H.M. (2001). Information Availability in 2D and 3D Displays. *IEEE Computer Graphics and Applications* Vol. 21(5): 51-57.

Stevens, S.S. (1957). On the psychophysical law. *Psychological Review* Vol. 64(3): 153-181.

Talmy, L. (1983). How language structures space. *Spatial Orientation - Theory Research and Application*. Pick, H.L. and Acredolo, L.P., Eds. New York, Plenum Press: 225-282.

Tastle, W.J. and Wierman, M.J. (2006). An information theoretic measure for the evaluation of ordinal scale data. *Behavior Research Methods* Vol. 38(3): 487-494.

Thomas, J.J. and Cook, K.A. (2005). *Illuminating the Path: Research and Development Agenda for Visual Analytics*, IEEE Press.

Tobler, W. (1987). Experiments in Migration Mapping by Computer. *The American Cartographer* Vol. 14(2): 155-163.

Tomkiewicz, S.M., Fuller, M.R., Kie, J.G. and Bates, K.K. (2010). Global positioning system and associated technologies in animal behaviour and ecological research. *Philosophical Transactions of The Royal Society Biological Sciences* Vol. 365: 2163-2176.

Tversky, B. and Bauer Morrison, J. (2002). Animation: can it facilitate? *International Journal Human Computer Studies* Vol. 57: 247-262.

Tversky, B., Zacks, J.M. and Martin Hard, B. (2008). The Structure of Experience. *Understanding Events - From Perception to Action*. Shipley, T.F. and Zacks, J.M., Eds. Oxford, Oxford University Press: 436-464.

van Wijk, J.J. and van Selow, E. (1999). Cluster and calendar based visualization of time series data. *IEEE Symposium on Information Visualization*. San Francisco, CA: 4-9.

Vasiliev, I.R. (1997). Mapping Time. *Cartographica* Vol. 34(2): 1-51.

Weaver, C. (2008). *Cross-dimensional Visual Queries for Interactive+Animated Analysis of Movement*. GIScience Pre-Conference Workshop on GeoSpatial Visual Analytics, Park City, UT, Sep. 23-26, 2008.

Weber, M., Alexa, M. and Müller, W. (2001). *Visualizing Time-Series on Spirals*. IEEE Symposium on Information Visualization, San Diego, CA: 7-13.

Wickens, C.D. and Hollands, J.G. (1999). *Engineering Psychology and Human Performance*. Upper Saddle River, NJ, Prentice Hall.

Worboys, M. (2005). Event-oriented approaches to geographic phenomena. *International Journal of Geographical Information Science* Vol. 19(1): 1-28.

Worboys, M. and Hornsby, K. (2004). *From objects to events: GEM, the geospatial event model.* GIScience, Springer: 327-343.

Yan, Z., Macedo, J., Parent, C. and Spaccapietra, S. (2008). Trajectory Ontologies and Queries. *Transactions in GIS* Vol. 12(1): 75-91.

Yattaw, N.J. (1999). Conceptualizing Space and Time: A Classification of Geographic Movement. *Cartography and Geographic Information Science* Vol. 26(2): 85-98.
Yu, H. (2006). Spatio-temporal GIS Design for Exploring Interactions of Human Activities. *Cartography and Geographic Information Science* Vol. 33(1): 3-19.
Yu, H. and Shaw, S.-L. (2007). Revisiting Hägerstrand's time-geographic framework for individual activities in the ago of instant access. *Societies and Cities in the Age of Instant Access*. Miller, H.J., Ed. Dordrecht, The Netherlands, Springer Science: 103-118.
Zacks, J.M. (2004). Using movement and intentions to understand simple events. *Cognitive Science* Vol. 28: 979-1008.
Zacks, J.M., Kumar, S., Abrams, R.A. and Mehta, R. (2009). Using movement and intentions to understand human activity. *Cognition* Vol. 112: 201-216.
Zacks, J.M. and Tversky, B. (2001). Event Structure in Perception and Cognition. *Psychological Bulletin* Vol. 127(1): 3-21.
Zhao, J., Forer, P. and Harvey, A.S. (2008). Activities, ringmaps and geovisualization of large human movement fields. *Information Visualization* Vol. 7(3): 198-209.

Appendix

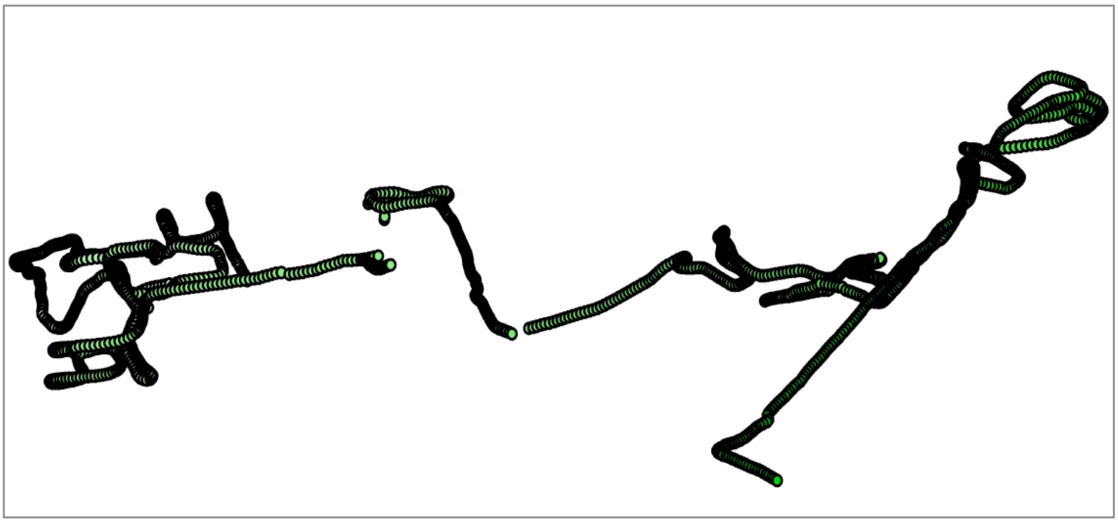
Questions and Stimuli for Experiment I

1) Können Sie ein Muster in diesem Bewegungspfad entdecken? (yes/no)
2) Was Ja, was für einMuster können Sie entdecken? (open text box)
3) Welches Objekt hat Ihrer Meinung nach diesen Bewegungspfad hinterlassen? (animal/human/eyes)
4) Was hat das Objekt Ihrer Meinung nach gemacht? (food search/ information search/shopping/walking/biking/defending)
5) Wie lang ist Ihrer Meinung nach die Dauer der Bewegung? (1 min/1 hr/1 day/1 month/1 season/1yr)
6) Wie gross ist Ihrer Meinung nach die Fläche die das Objekt gebraucht hat? (1qm/ 100 qm/ 1ha/ 10qkm/ 100qkm)
7) In wie fern halten Sie die folgenden Aspekte für relevant und wichtig für Ihre Analyse? (Scale from Gar nicht/wenig/indifferent/viel/sehr viel)
    a. Unregelmässigkeiten
    b. Muster
    c. Wendungen
    d. Länge
    e. Kreuzungen
8) An welchem Punkt war Ihrer Meinung das Objekt am langsamsten? (A/B/C)
9) Beurteilen Sie die Distanz von A zu B und von C zu D. Welche Distanz ist länger? (A zu B/ C zu D/Sie sind gleich lang)
10) Wo denken Sie hat das Objekt eine Pause gemacht? (A/B/C)
11) Wann hat das Objekt in Ihren Augen beschleunigt? (A/B/C)
12) Hat das Objekt Ihrer Meinugn nach genauso lange gebraucht von A nach B wie von B nach C? (Ja, genauso lang/Nein, länger/Nein, kürzer/Ich bin mir nicht sicher)
13) Wann war das Objekt Ihrer Meinung nach am Schnellsten? (A/B/C)
14) Beurteilen Sie die Distanz von A zu B im Vergleich zu B zu C. Ist die Distanz gleich gross? (Ja, etwa gleich gross/Nein, von A zu B ist länger/ Nein, von A zu B ist kürzer)
15) Wann ist das Objekt Ihrer Meinung nach langsamer geworden? (A/B/C)
16) An welchem Ort hat das Objekt in Ihren Augen etwas Unerwartetes gemacht? (A/B/C)
17) Hat das Objekt Ihrer Meinung nach länger von A zu B oder von C zu D gebraucht? (Von A zu B dauert länger/Von A zu B dauert weniger lang/Es dauert etwa gleich lang)
18) An welchem Punkt war das Objekt Ihrer Meinung nach am Schnellsten? (A/B/C)
19) Wieviel länger hat das Objekt in Ihren Augen von A zu B im Vergleich von C zu D gebraucht? (gleich lang/doppelt so lang/halb so lang)
20) Wo verbringt das Objekt die meiste Zeit? (A/B/C)
21) Wann hat das Objekt in Ihren Augen beschleunigt? (A/B/C)
22) Wieviel grösser ist die Distanz von A zu B im Vergleich von C zu D? (gleich gross/doppelt so gross/halb so gross)
23) Arbeiten Sie regelmässig mit Bewegungsdaten? (Ja/Nein)
24) Wenn Ja, mit was für Daten arbeiten Sie? (open text box)

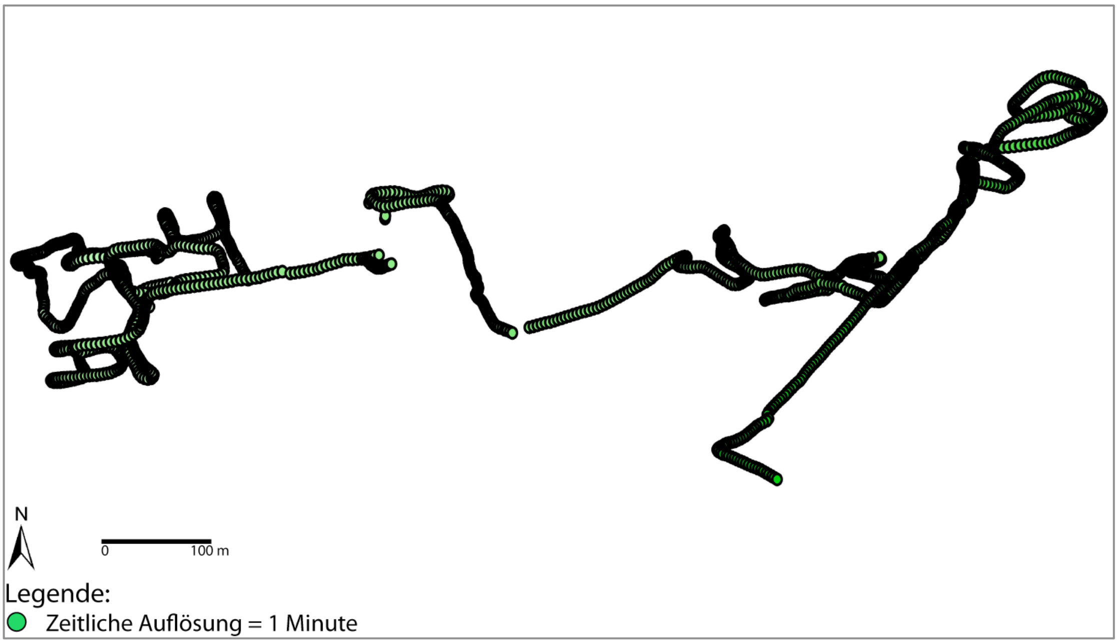
25) Sind Sie mit Software zur Analyse von Bewegungsdaten vertraut, z. B. Esri Tracking Analyst?
26) Wenn Ja, welche Software benutzen Sie?
27) Wie oft benutzen Sie Software zur Analyse von Bewegungsdaten? (immer/sehr oft/oft/gelegentlich/selten/sehr selten/nie)
28) Ihr Geschlecht: (Mann/Frau)
29) Ihr Alter: (20-30/31-40/41-60/60+)
30) Haben Sie noch kritische Anmerkungen oder Fragen?

Stimuli for overall analysis:

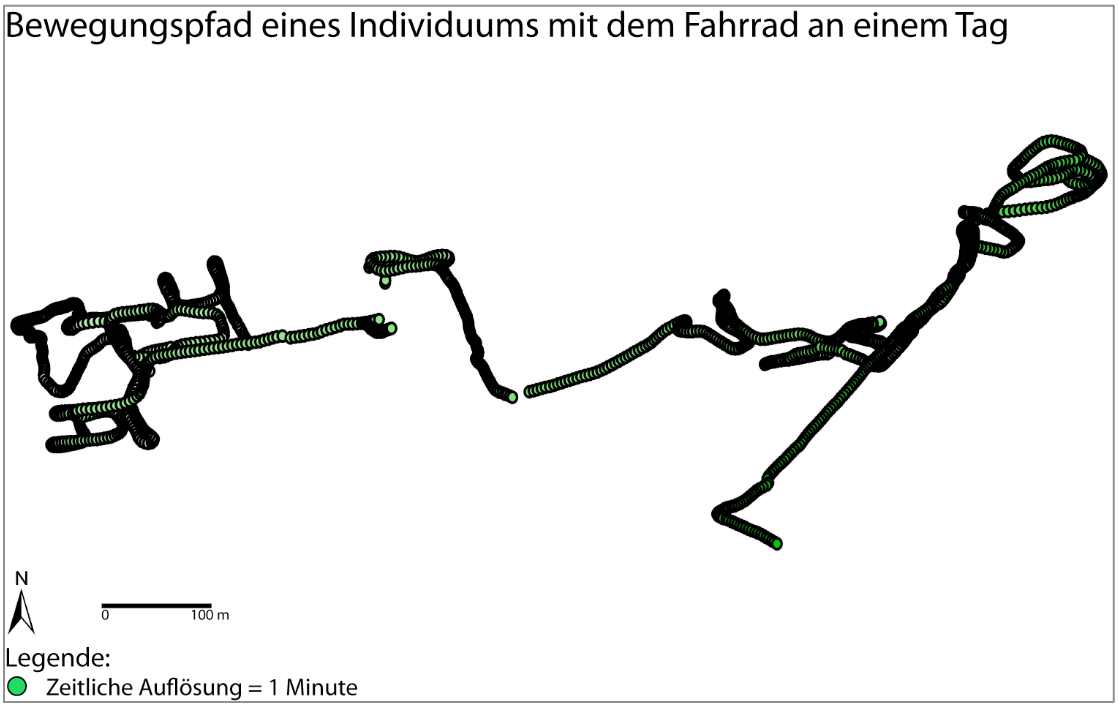
Wihout context condition:



With legend:

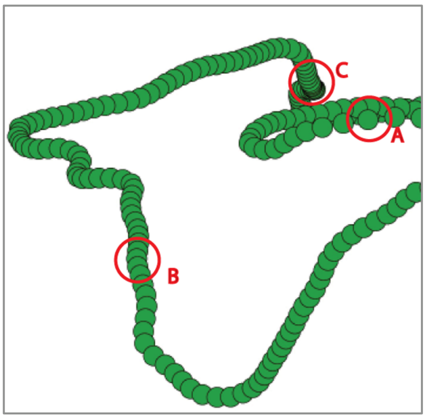


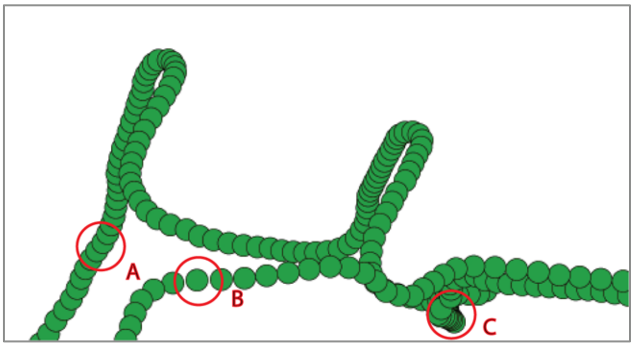
With legend and title:



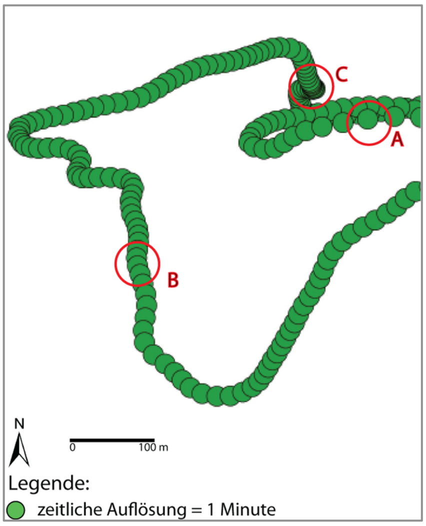
Two Exemplary Stimuli for Detailed Analysis

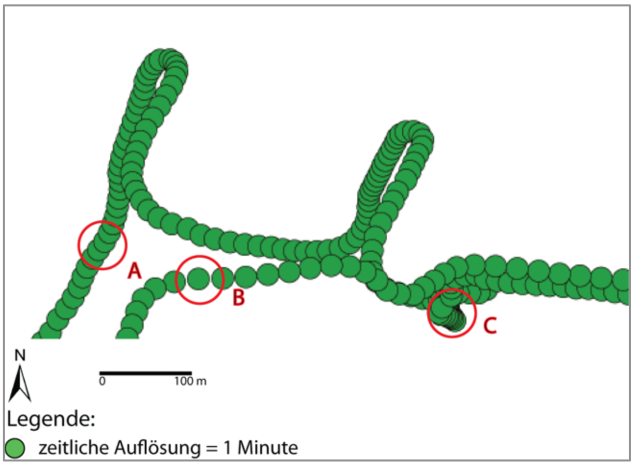
Without context information:



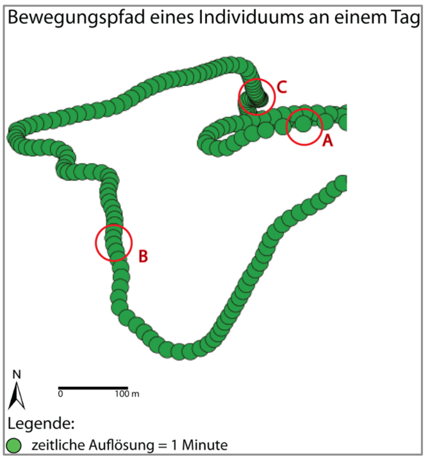


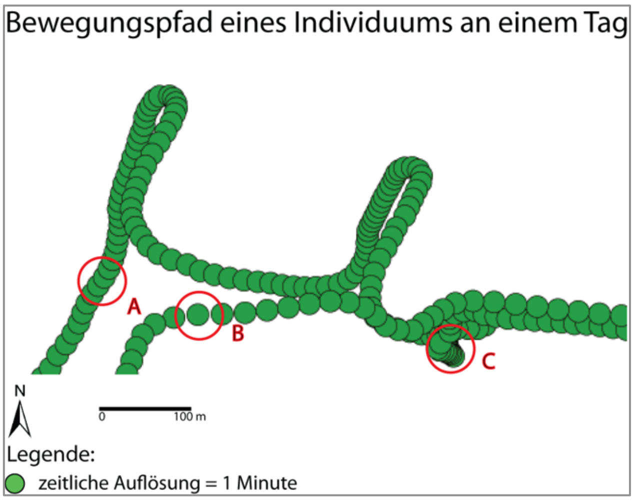
With legend information:





With title and legend information





All remaining stimuli can be found on the CD.

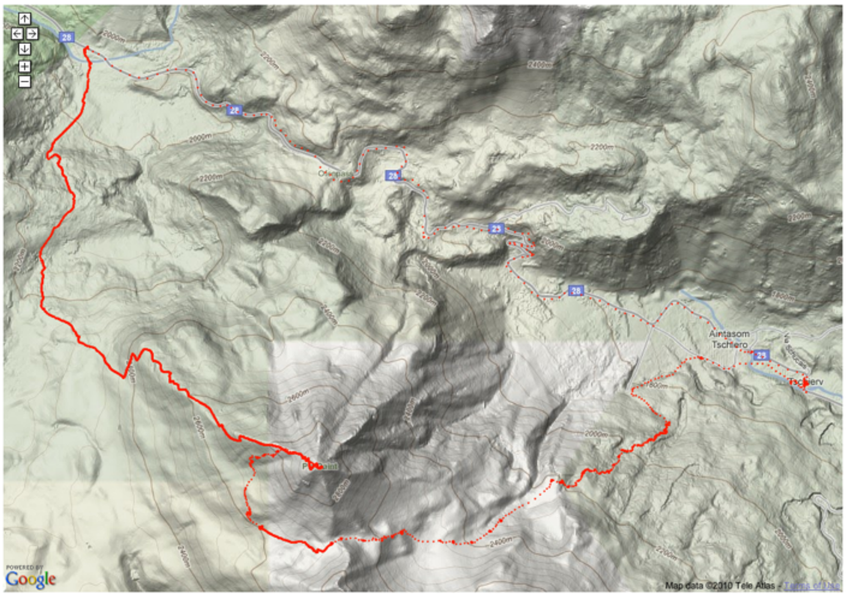
Randomization Function for Experiment II

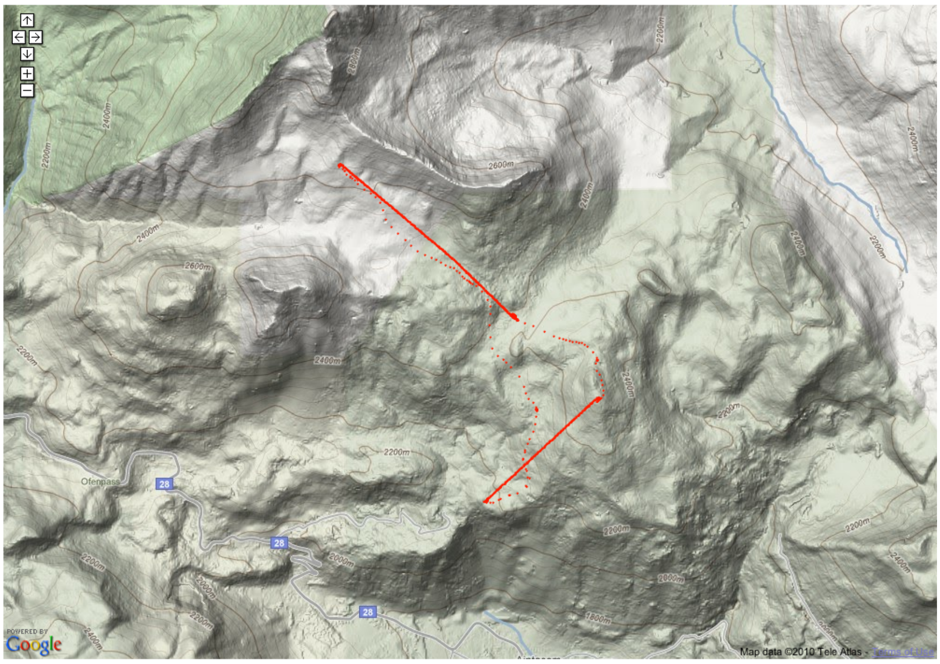
```
<?php //start php script
        $random = rand(1, 3);
        $uid = time();

        $countFile = "countfile_questionnaire_AK.txt";
        $countHandle = fopen($countFile, 'a');
        $data = $random."\n";
        fwrite($countHandle, $data);
        fclose($countHandle);

        $logFile = "logfile_questionnaire_AK.txt";
        $logHandle = fopen($logFile, 'w');
        fwrite($logHandle, $uid);
        fclose($logHandle);

        if ($random == 1){
        echo "<p><a
href='http://www.onlineumfragen.com/login.cfm?umfrage=12212'>Starte das Experiment
(Gruppe ".$random.", www.onlineumfragen.com/login.cfm?umfrage=12212)...</a>";
        }
        elseif ($random == 2){
        echo "<p><a
href='http://www.onlineumfragen.com/login.cfm?umfrage=12209'>Starte das Experiment
(Gruppe ".$random.", www.onlineumfragen.com/login.cfm?umfrage=12209)...</a>";
        }
        else { //$random == 3
        echo "<p><a
href='http://www.onlineumfragen.com/login.cfm?umfrage=12172'>Starte das Experiment
(Gruppe ".$random.", www.onlineumfragen.com/login.cfm?umfrage=12172)...</a>";
        }
// end of php script
?>
```

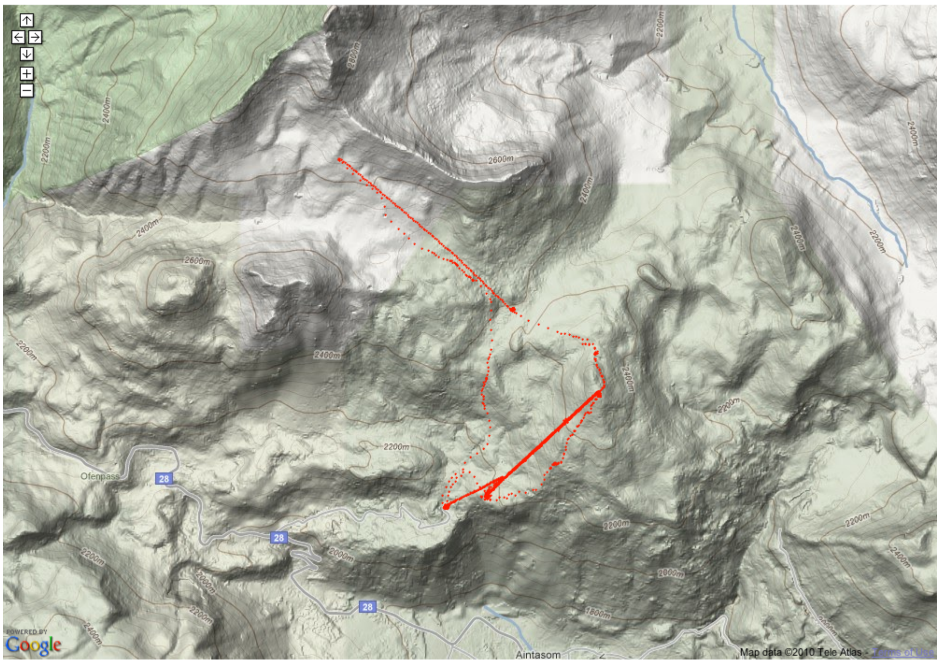
Stimuli for Experiment II & III

Example Stimuli with context information

(all had equal size in Experiment)




2600m
2400m
2200m
Ofenpass
28
Map data ©2010 Tele Atlas


2600m
2400m
2200m
Ofenpass
28
Aintasom
Map data ©2010 Tele Atlas

Functions.js:

The copyright belongs to Ramya Venkateswaran, from the GIS unit of the Department of Geography, who programmed the functions.js code as well as an initial track.php function.

```
// The copyright of this code belongs to: Ramya Venkateswaran, GIS Unit, Department of
Geography, University of Zurich
/*
Index number;Time stamp;Lat;Long;Circle size

1;10/5/2010 18:30:45;;Circle 1
*/
var xmlDoc;
var URL;
var latLng=new Array();
var markers = new Array();
var map;
var text;
var count =1;
var kml;

function randomUrl(url) {
	var date = new Date();
	return url + "?" + date.valueOf();
}


function initialize(fileName) {
	if (GBrowserIsCompatible()) {
	map = new GMap2(document.getElementById("map_canvas"));
	map.setMapType(G_PHYSICAL_MAP);
      // add controls
	GEvent.addListener(map, "click", click);
	map.disableDragging();
	loadXML(fileName + ".xml");
	//Create all the overlays here
	geoXmlTent = new GGeoXml(
		randomUrl("http://www.geo.uzh.ch/~annakl/EventExperiment/Context_Tent_" +
fileName + ".kmz"));
    //For every overlay you create you have to add it using addOverlay
		map.addOverlay(geoXmlTent);

}
}

function click(latlng, overlaylatlng, overlay){

	var shape;
	var radius;
	if (document.getElementById("circle2").checked)
	{
		radius = 0.08;
		shape="circle";
	}

	if (overlay != null)
```

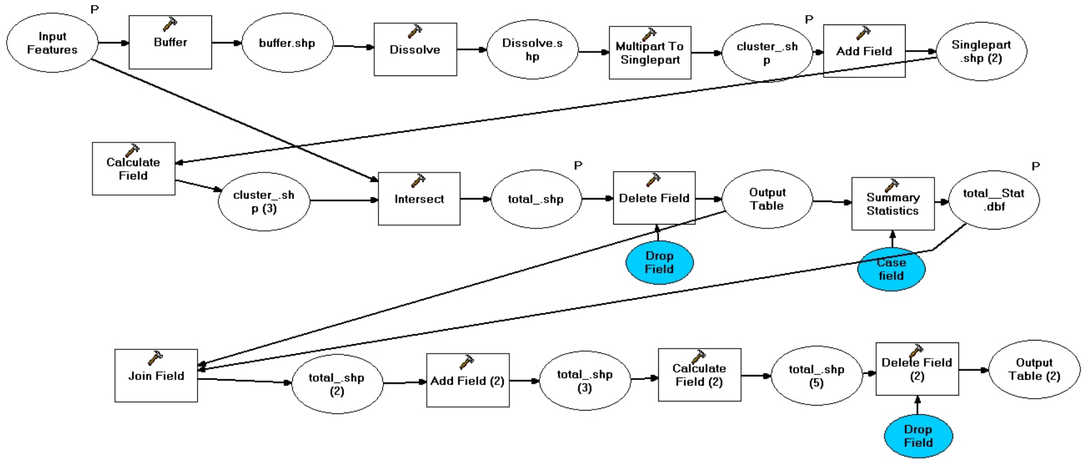
```
	{
		if(shape == "circle"){
			drawCircle(overlay,radius);
			writeToTextBox(overlay, radius);
		}

	}

}

function writeToTextBox(overlay, radius){

	if (count == 1)
	{
		text = "";
	}
	var shape = "";

	if(document.getElementById("circle2").checked == true)
	{
		shape = "circle2";
	}


	text  = count.toString() + ";" + overlay + ";" + radius +  ";" + shape + "\r\n";
	count++;
	//alert(text);
	document.getElementById("mapData"). value = document.getElementById("mapData").
value + text;
}

function drawCircle(center,radius){
	var circlePoints = Array();
	var searchPoints = Array();
	var pointInterval = 30;


	with (Math) {
		var rLat = (radius/3963.189) * (180/PI); // miles
		var rLng = rLat/cos(center.lat() * (PI/180));

		for (var a = 0 ; a < 361 ; a++ ) {
			var aRad = a*(PI/180);
			var x = center.lng() + (rLng * cos(aRad));
			var y = center.lat() + (rLat * sin(aRad));
			var point = new GLatLng(parseFloat(y),parseFloat(x),true);
			circlePoints.push(point);
			if (a % pointInterval == 0) {
				searchPoints.push(point);
			}
		}
	}

	searchPolygon = new GPolygon(circlePoints, '#0000ff', 1, 1, '#0000ff', 0.2);
	map.addOverlay(searchPolygon);
}

function drawRectangle(center,diagonal){

   var breadth = diagonal*2;
   var length = diagonal;

	var polygon = new GPolygon([
    new GLatLng(center.lat() - (length/2) , center.lng() - (breadth/2)),
    new GLatLng(center.lat() + (length/2) , center.lng() - (breadth/2)),
```

```
    new GLatLng(center.lat() + (length/2) , center.lng() + (breadth/2)),
    new GLatLng(center.lat() - (length/2) , center.lng() + (breadth/2)),
    new GLatLng(center.lat() - (length/2) , center.lng() - (breadth/2)),
  ],  '#0000ff', 1, 1, '#0000ff', 0.2);

      //searchPolygon = new GPolygon(circlePoints, '#0000ff', 1, 1, '#0000ff', 0.2);
      map.addOverlay(polygon);
}


function loadXML(file){
    if (window.ActiveXObject){
        xmlDoc = new ActiveXObject("Microsoft.XMLDOM");
        xmlDoc.async="false";
        xmlDoc.load(file);
        if(xmlDoc.parseError.errorCode != 0)
            displayParseError_IE();
       else
            processDocumentIE();
    }
    else
    {

            var xmlhttp = new window.XMLHttpRequest();
            xmlhttp.open("GET",file,false);
            xmlhttp.send(null);
            xmlDoc = xmlhttp.responseXML.documentElement;
            //alert(xmlhttp.responseXML);
            processDocument();

    }
}

function displayParseError_IE()
{
      if (xmlDoc.parseError.errorCode != 0)
      {
            var popupHandle = window.open("","","height = 300, width = 400");
            popupHandle.document.write("<h2> XML Parsing Error! </h2><br>");
            popupHandle.document.write("Error#:" + xmlDoc.parseError.errorCode);
            popupHandle.document.write('<br>');
            popupHandle.document.write('Description:' + xmlDoc.parseError.reason);
            popupHandle.document.write('<br>');
            popupHandle.document.write('In file#:' + xmlDoc.parseError.url);
            popupHandle.document.write('<br>');
            popupHandle.document.write('Line#:' + xmlDoc.parseError.line);
            popupHandle.document.write('<br>');
            popupHandle.document.write('Character # in Line:' +
xmlDoc.parseError.linepos);
            popupHandle.document.write('<br>');
            popupHandle.document.write('Character # in File:' +
xmlDoc.parseError.filepos);
            popupHandle.document.write('<br>');
            popupHandle.document.write('Source Line:' + xmlDoc.parseError.srcText);
            popupHandle.document.write('<br>');
      }
}

function processDocument()
{
    var bounds = new GLatLngBounds();
      var tracks = xmlDoc.getElementsByTagName("track");

      map.setCenter(bounds.getCenter(),3);
    //alert(tracks.length);
```

```
        // Create our "tiny" marker icon
        var blueIcon = new GIcon();
        blueIcon.image = "../images/Untitled-2.gif";
        blueIcon.shadow = "";
        blueIcon.iconSize = new GSize(2,2);
        blueIcon.shadowSize = new GSize(0,0);
        blueIcon.iconAnchor = new GPoint(0,0);
        blueIcon.infoWindowAnchor = new GPoint(0,0);

        var i,j;
        var lat, lng;
        var mgr = new MarkerManager(map);

        var marker = new GMarker(new GLatLng(0.0, 0.0), {icon: blueIcon});
        var markerArray = [];
        markerArray.push(marker);
        mgr.addMarkers(markerArray, 3);
        mgr.refresh();

        for (i=0;i<tracks.length;i++)
        {
                var children = tracks[i].childNodes;
                var traversed = false;

                for (j=0;j<children.length;j++)
                {
                        if (children[j].nodeName == "latitude")
                        {
                                //alert(j);
                                lat = children[j].firstChild.nodeValue;
                        }
                        if (children[j].nodeName == "longitude")
                        {
                                //alert(j);
                                lng = children[j].firstChild.nodeValue
                        }
                        if ((lat != null) && (lng != null) && traversed==false)
                        {
                                latLng.push(new GLatLng(parseFloat(lat), parseFloat(lng)));
                                bounds.extend(latLng[i]);
                                traversed = true;
                                //map.addOverlay(new GMarker(latLng[i]), markerOptions);
                                var marker = new GMarker(latLng[i], {icon:blueIcon});
                                markers.push(marker);

                        }
                }
        }
        mgr.addMarkers(markers,3);
        mgr.refresh();
        map.setCenter(bounds.getCenter(),13);

}
```

The first step is the initialization of the google maps. Next, the *.xml file that contains trajectory information is initialized by loading the *.xml from the track.php file by calling the loadXML function. LoadXML() is responsible for any input/output (I/O) ooperations performed on the xml file.. The initialize function also calls the processDocument() function. This function handles the plotting of the trajectory from the XML file onto the google map using a couple of Google Maps API. Additionally a listener is initialized that is triggered when the user clicks on the map area. In this case it also checks if the radio button is activated in the track.php file. If a radio button is activated the click() function calls the drawCircles() and writeToTextBox() functions. The drawCircles() function takes the size of the circle and places it at the center of the mouse tip. It also makes sure that a circle can only been drawn if the mouse is on the trajectory. No circles can be drawn if the mouse is clicked outside the trajectory. The function also displays the circle on the map, which is important, as participants are able to draw more than one circle. The writeToTextBox() function is an internal function that saves the parameters that were used. It also connects to the track.php file and writes all the circles that were drawn, including timestamp, longlitude, latidue into a file.

ArcMap Clustering



Curriculum Vitae

Name Anna-Katharina **LAUTENSCHÜTZ**

Geboren am 25.03.1980

Geboren in Recklinghausen, Deutschland

Gymnasium 1990 – 1999

am Hittorf Gymnasium in Recklinghausen, Deutschland

Bilinguales Abitur 1999

Studium 1999 - 2006

Westfälische Wilhelms-Universität Münster

Diplom in Geographie 2006

Diplomarbeit: Spatial Relations – The influence of scale, context, and spatial relation in linguistic topology

Doktorat 2007 – 2011

am Geographischen Institut der Universität Zürich

als Doktorandin angestellt: März 2007

Publikationen mit unmittelbarem Bezug zur Dissertation

Dodge, S., Weibel, R. & **Lautenschütz, A.-K.** (2008): Towards a Taxonomy of Movement Patterns. Information Visualization 7, pp. 240-252 [pdf]

Anna-Katharina Lautenschütz, Sara Irina Fabrikant (2008): Towards a cognitive conceptual framework of movement, Agile Workshop 2008 "Geovisualization of Dynamics, Movement and Change", May 5-8th 2008, Girona, Spain [pdf]

Anna-Katharina Lautenschütz (2009): Evaluating the importance of contextual information in visual displays of movement patterns, COSIT Doctoral Colloquium 2009, September 21-25th 2009, Aber Wrac'h, France [pdf]

Anna-Katharina Lautenschütz (2010): How context influences the segmentation of movement trajectories - an experimental approach for environmental and behavioral context, GIScience 2010, September 14-18th 2010, Zurich, Switzerland. Extended Abstracts online proceedings: http://www.giscience2010.org/index.php?page=content